UNIVERSITY OF PLYMOUTH

Cooperative Swarm Optimisation of Unmanned Surface Vehicles

by

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"There's nothing wrong with enjoying looking at the surface of the ocean itself, except that when you finally see what goes on underwater,you realize that you've been missing the whole point of the ocean. Staying on the surface all the time is like going to the circus and staring at the outside of the tent."

Dave Barry

Abstract

Cooperative Swarm Optimisation of Unmanned Surface Vehicles

With growing advances in technology and everyday dependence on oceans for resources, the role of unmanned surface vehicles (USVs) has increased many fold. Extensive operations of USVs having naval, civil and scientific applications are currently being undertaken in various complex marine environments and demands are being placed on them to increase their autonomy and adaptability. A key requirement for the autonomous operation of USVs is to possess a multi-vehicle framework where they can operate as a fleet of vehicles in a practical marine environment with multiple advantages such as surveying of wider areas in less time. From the literature, it is evident that a huge number of studies has been conducted in the area of single USV path planning, guidance and control whilst very few studies have been conducted to understand the implications of the multi vehicle approaches to USVs. This present PhD thesis integrates the modules of efficient optimal path planning, robust path following guidance and cooperative swarm aggregation approach towards development of a new hybrid framework for cooperative navigation of swarm of USVs to enable optimal and autonomous operation in a maritime environment.

Initially, an effective and novel optimal path planning approach based on the A* algorithm has been designed taking into account the constraint of a safety distance from the obstacles to avoid the collisions in scenarios of moving obstacles and sea surface currents. This approach is then integrated with a novel virtual target path following guidance module developed for USVs where the reference trajectory from the path planner is fed into the guidance system. The novelty of the current work relies on combining the above mentioned integrated path following guidance system with decentralised swarm aggregation behaviour by means of simple potential based attraction and repulsion functions to maintain the centroid of the swarm of USVs and thereby guiding the swarm of USVs onto a reference path. Finally, an optimal and hybrid framework for cooperative navigation and guidance of fleet of USVs, implementable in practical maritime environments and effective for practical applications at sea is presented.

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Authors Declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Doctoral College Quality Sub-Committee.

Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at the University of Plymouth or at another establishment.

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Relevant scientific seminars and conferences were regularly attended at which the work carried out was presented. A list of publications and presentations can be found below.

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In order to pursue the research objectives and making a contribution to existing knowledge, findings have been disseminated in a series of publications including journal papers, conference proceedings, book chapter and presentations. The following comprises a list of papers published or under review for publication:

Journal Papers

1. **Singh, Y.**, Sharma, S., Hatton, D., and Sutton, R. Optimal Path Planning of Marine Vehicles .Indian Journal of Geo-Marine Sciences, 47(07), Pages 1325-1334, July 2018. (URI: http://nopr.niscair.res.in/handle/123456789/44622)

2. **Singh, Y.**, Sharma, S., Hatton, D., and Sutton, R. Towards use of Dijkstra Algorithm for Optimal navigation of an Unmanned Surface Vehicle in a Real-Time Marine Environment with results from Artificial Potential Field .International Journal on Marine Navigation and Safety of Sea Transportation, 12(1), Pages 125-131, 2018. (DOI: 10.12716/1001.12.01.14)

3. Szyrowski, T., Bogdan, P., Khan, A., Pemberton, A., Sharma, S., **Singh, Y.** and Riccardo, P. Range Extension for Electromagnetic Detection of Subsea Power and Telecommunication Cables. Under Review in Journal of Marine Engineering and Technology.

4. **Singh, Y.**, Sharma, S., Hatton, D., Sutton, R. and Khan, A. A constrained A* approach towards optimal path planning of an unmanned surface vehicle in a maritime environment containing dynamic obstacles and ocean currents. Ocean Engineering, 169, Pages 187-201, 2018.(DOI: https://doi.org/10.1016/j.oceaneng.2018.09.016)

Conference papers and presentations

1. **Singh, Y.**, Polvara, R., Sharma, S., Hatton, D., Sutton, R. and Wan, J. Design of a Variable Buoyancy Engine for Small Scale Underwater Vehicle. International Conference on Advances in Subsea Engineering, Structures and Systems (ASESS-2016), 6-7th June 2016, Glasgow, UK.

2. Abed, W., Polvara, R., **Singh, Y.**, Sharma, S., Hatton, D., Andrew, M., Sutton, R. and Wan, J. Advanced Feature Extraction and Dimensionality Reduction for Unmanned Underwater Vehicle Fault Diagnosis. 11th UKACC (United Kingdom Automatic Control Council) International Conference on Control, 31st August - 2nd September, 2016, Belfast, Northern Ireland, UK.(DOI: 10.1109/CONTROL.2016.7737596).

3. **Singh, Y.**, Sharma, S., Hatton, D., and Sutton, R. Path Planning of an Autonomous Surface Vehicle based on Artificial Potential Fields in a Real-Time Marine Environment. 16th International Conference on Computer and IT Applications in the Maritime Industries (COMPIT 2017), 15-17th May, Cardiff, UK. (URL: http://data.hiper-conf.info/compit2017_cardiff.pdf)

4. **Singh, Y.**, Sharma, S., Hatton, D., and Sutton, R. Optimal Path Planning of an Autonomous Unmanned Vehicle in a Real-Time Marine Environment using Dijkstra Algorithm. International Conference on Marine Navigation and Safety of Sea Transportation (TransNav 2017), 21-23rd June. Gdynia, Poland. (DOI: http://dx.doi.org/10.1201/9781315099132-70)

5. Szyrowski, T., Bogdan, P., Khan, A., Pemberton, R., Sharma, S.K., **Singh, Y.**, Polvara, R. Range Extension for Electromagnetic Detection of Subsea Power and

Telecommunication Cables. International Conference on Marine Electromagnetics (MARELEC 2017), 27-30th June, 2017, Liverpool, UK.

6. **Singh, Y.**, Sharma, S., Hatton, D., and Sutton, R. USV Navigation in a Real-Time Map using Intelligent Path Planner. 2nd International Conference on Mechatronics, Automation and Smart Materials, 13-14th November 2017, Paris, France. (DOI: https://doi.org/10.4172/2168-9873-C1-014)

7. **Singh, Y.**, Sharma, S., Hatton, D., and Sutton, R. Feasibility study of a Constrained Dijkstra Approach for Optimal Path Planning of an Unmanned Surface Vehicle in a Dynamic Maritime Environment. 18th IEEE International Conference on Autonomous Robot Systems and Competitions. (Apr. 25-27,2018). Torres Vedras, Portugal, 2018.(DOI: 10.1109/ICARSC.2018.8374170)

8. Bibuli, M., **Singh, Y.**, Sharma, S., Sutton, R, Hatton, D., and Khan, A. A Two Layered Optimal Approach towards Cooperative Motion Planning of Unmanned Surface Vehicles in a Constrained Maritime Environment. 11th IFAC Conference on Control Applications in Marine Systems, Robotics, and Vehicles - CAMS 2018 (Sep 10-12,2018), Opatija, Croatia, 2018.(DOI: https://doi.org/10.1016/j.ifacol.2018.09.458)

9. **Singh, Y.**, Sharma, S., Hatton, D., and Sutton, R. Artificial Potential Field for Path Planning of an Uninhabited Surface Vehicle in a Real-Time Marine Environment. Invited Presentation at UK Robotics Week, 30th June, 2016, Plymouth, UK.

10. **Singh, Y.**, Steve, R. Collaborative Marine Autonomy. Invited Presentation at Year of Autonomy Event by QinetiQ (Portsdown Technology Park), 28th February 2017, Portsmouth, UK.

11. **Singh, Y.**. A Two-Layered Optimal Approach towards Cooperative Motion Planning of Unmanned Surface Vehicles in a Constrained Maritime Environment. Invited Presentation at CSC Research Scholar Day (University of Nottingham), 03rd August 2018, Nottingham, UK.

Book chapter

1. **Singh, Y.**, Sharma, S., Hatton, D., Sutton, R. and Khan, A. Efficient Optimal Path Planning of Unmanned Surface Vehicles". In: Navigation and Control of Autonomous Marine Vehicles. Ed. by Sanjay Sharma and Bidyadhar Subudhi. Stevenage: IET, 2018. Chap. 9.

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Abbreviations

ACO	Ant Colony Algorithm
ACTRESS	ACTor-based Robots and Equipments Synthetic System
AMS	Autonomous Marine Systems
AOSN	Autonomous Ocean Sampling Network
APF	Artificial Potential Field
AUVs	Autonomous Underwater Vehicles
COLREGs	The International Regulations for Preventing Collisions at Sea
DPSS	Direct Priority Sequential Selection
DOA	Deliberative Obstacle Avoidance
DoD	Department of Defense
FAO	Fly Optimisation Algorithm
FM	Fast Marching
GNRON	Goal Non Reachable With Obstacles Nearby
GPS	Global Positioning System
IFAC	International Federation of Automatic Control
IJGMS	Indian Journal of Geo-Marine Sciences
IMO	International Maritime Organisation
LOS	Line of Sight
LQG	Linear Quadratic Gaussian
MASRWG	Maritime Autonomous Systems Working Group
MPC	Model Predictive Control
NSB	Null Space Based
ODA	Obstacle Detection and Avoidance
PID	Proportional Integral Derivative
PSO	Particle Swarm Algorithm
ROA	Reactive Obstacle Avoidance
ROVs	Remotely Operated Vehicles
RRT	Rapidly-Exploring Random Trees

SLAM	Simultaneous Localisation and Mapping
SOM	Self Organising Map
UAVs	Unmanned Aerial Vehicles
UGVs	Unmanned Ground Vehicles
UK	United Kingdom
US	United States
USVs	Unmanned Surface Vehicles
UUVs	Unmanned Underwater Vehicles
WP	Waypoints

Physical Constants

F_{att}	attractive force	(N)
F_{rep}	repulsive force	(N)
U_{att}	quadratic attractive potential	(N)
U_{rep}	repulsive potential	(N)
K_{att}	proportionality constant	
K_{rep}	proportionality constant	
K_{ρ}, K_{ν}	tunable controller parameter	
K_{sat}	saturation gain	

Symbols

Chapter 3

x	current position of robot
G	goal
$\|.\|$	Euclidean distance function
$u()$	unit vector
o_i	position of the obstacle
d^*	safety distance from obstacle
Q	vertex set
v	vertex
u	intermediate vertex in graph

Chapter 4

$f(n)$	overall heuristic cost
$g(n)$	heuristic distance of the cell to the goal state
$h(n)$	length of the path from initial state to goal state through selected sequence of cells

Chapter 5

γ	non dimensional polynomial parameter
X	set
n	number of robots
$x_i(t)$	vector associated with each robot
$\tilde{x}(t)$	instantaneous barycenter of the swarm
$\epsilon_i(t)$	vector distance of each robot from the center
$X(t)$	collection of all robots
$\epsilon(t)$	collection of distances of the robot from the barycenter
G_i	proximity graph
V	set of robots
E	set of edges representing communication channel between the robots and the center
i, j	nodes representing robots in a 2D plane
R_{ij}	visibility range

$L(G_i)$	Laplacian matrix associated with the graph G
$\Delta(G_i)$	degree diagonal matrix of $n \times n$ elements
$A(G_i)$	adjacency matrix of $n \times n$ elements
$< e >$	earth fixed reference frame
$< b >$	body fixed reference frame
$[x\ y\ z\ \Psi]$	position and orientation of the USV
$[u_r\ v_r]$	relative surge and sway velocity of the USV with respect to the water
r	yaw rate
$[\dot{x_c}\ \dot{y_c}]$	sea current
P	position vector with respect to $< e >$ frame represented by $P = [x_p\ y_p\ 0]$
B	position vector with respect to $< f >$ frame represented by $B = [s_1\ y_1\ 0]$
Ψ_e, Ψ_f	orientation of the USV in $< e >$ and $< f >$ frame
U	resultant velocity of the USV in $< e >$
s	signed curvilinear abscissa along the path
$c_c(s)$	path curvature
$g_c(s)$	derivative of the path curvature
β	orientation difference between $< e >$ and $< f >$ frame
ρ, ν	linear error components
Ψ^*	reference guidance angle computed by the path-following module
V	Lyapunov function
$\dot{s}$	speed of the reference frame
Ψ_a	maximum approach angle with respect to Ψ_f
u_i^s	control effort required to reach a collective behavior for each USV
u^g	expected trajectory of the fleet centroid common to all the USV
u^*	desired speed for the formation along the path
$g(\cdot)$	function of attraction and repulsion between neighbouring robots
$g_a(\cdot)$	attractive function
$g_r(\cdot)$	repulsive contribution

For Parents

Chapter 1

Introduction

> *"There must be a beginning of any great matter, but the continuing unto the end until it be thoroughly finished yields the true glory"*
>
> Sir Francis Drake

This chapter outlines the aim and objectives of the research undertaken herein and presents an overview of the concepts that are developed throughout the thesis without inquiring much into the technical details. The main contributions of the research and a list of resulting publications are included in this introductory chapter.

1.1 Motivation

In the present economic world order, there is a greater need for exploring oceans for resources as well as for future needs. Historical ice coverage of the Arctic in September 2007 (Serreze et al., 2008) and in situ data collected from surface vehicles directing improvements in weather forecasting (Legrand et al., 2003) have shown the potential of USVs towards outlining a range of future missions. This has brought in the need to develop a heterogeneous multi-robot framework in a maritime environment, where a set of networked marine robots cooperatively coordinate to achieve the global objectives of a maritime mission. The advantages of such cooperative behaviour against a fully equipped single vehicle system ranges from wider surveying in less time, lowering the cost of each vehicle, higher robustness in critical missions and multi-objective mission planning through the allocation of different tasks to each vehicle in the mission (Liu and Bucknall, 2018b). In addition to that, these USVs can also act as communication node for underwater robots and aerial robots in a heterogeneous swarm deployed for surveying, monitoring and intelligence applications (Bibuli et al., 2014). The USVs communicate with underwater robots using acoustics and aerial robots using WiFi. Currently there is a need for higher autonomy in the maritime environment where such vehicles can operate in dynamic and uncertain circumstances. In this sense, a greater degree of implementable intelligence and general robustness is required to be incorporated into such a multi-vehicle framework, so that lesser human supervision is required in their operation as a fleet of USVs .

Two terms namely, *cost* and *practical maritime environment*, are being used hereafter to describe the performance of the approaches adopted in this thesis in the subsequent chapters. The term *cost* in the thesis refers to the amount of computational time required by the algorithms adopted in the thesis to obtain a solution. Whereas,the term *practical maritime environment* in the thesis refers to an extracted map from the real navigation map where the static and dynamic obstacles are realistically represented.

1.1.1 Brief panorama concerning cooperative behaviour of unmanned vehicles

Unmanned vehicles can be categorised on their mode of operation in four categories as Unmanned Aerial Vehicle (UAV), an Unmanned Ground Vehicle (UGV), an USV or an Autonomous Underwater Vehicle (AUV) . In the last decade or so, the research interest of the robotics community has focused on the study of multiple marine craft coordinating cooperatively in a global framework (as shown in Fig.1.1) to achieve mission goals globally and thereby covering wider mission areas for a longer duration. In particular, for military and naval applications, defence departments of the US and UK have already allocated budget and resources towards the development of cooperative framework for marine vehicles and their absolute integration to prospective combat zones (Royal Navy, 2016, US Military, 2010).

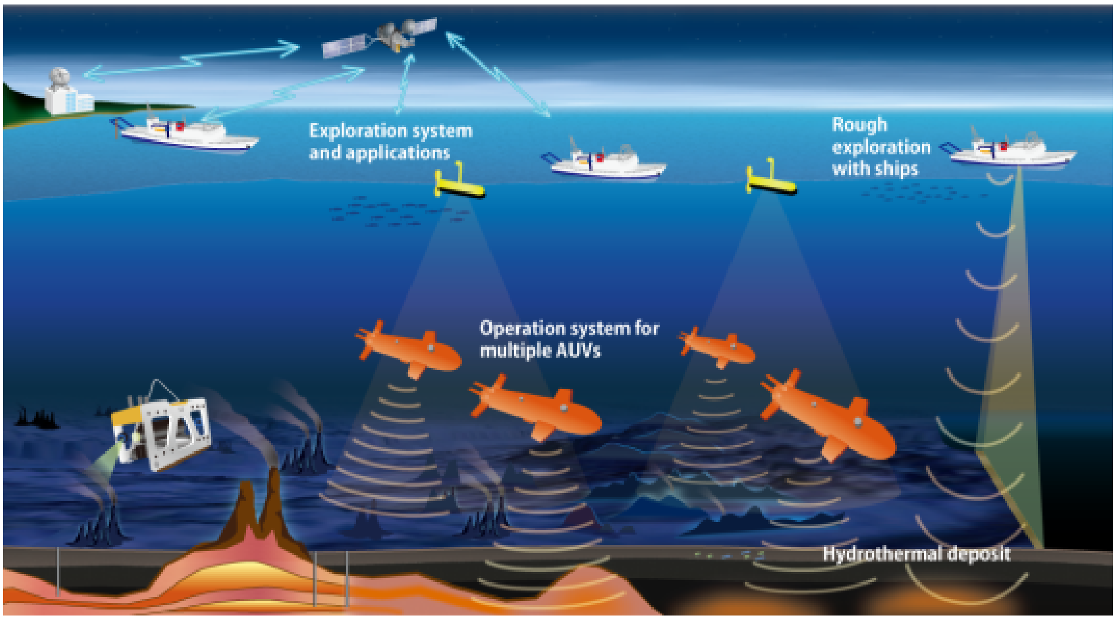


FIGURE 1.1: Integrated marine network (Source : *JAMSTEC Website*)

Two major research areas have been widely studied in understanding and implementing the cooperative behaviour of unmanned vehicles namely, formation control and cooperative motion planning.Initial studies towards deployment of a multi-vehicle system have been carried out in the area of formation control. In this area, control approaches generate appropriate control commands and drives multiple vehicles along desired route with certain vehicle constraints (Bai and Wen, 2010, Desai et al., 1998, Do, 2009). Major research in this has been towards consensus-based formation control, where retaining a certain shape during navigation is the primary objective. There are three major approaches associated with the formation control: the virtual structure approach, the behaviour-based approach, and the leader-following approach(Antonelli et al., 2009, Chen and Wang, 2005a, Tan and Lewis, 1996a). The major issues associated with these approaches are high computational cost, problems in describing the dynamics of the formation behaviour and maintaining control stability (Nascimento, 2012). These issues led to the developments in the area of cooperative motion planning, where the aim is to provide practical guidelines towards cooperative motion planning of multiple USVs such as optimal reference trajectories between start and goal points, less computational time and safety distance from the obstacles in addition to several factors associated with formation control (Bellingham et al., 2002, Tsourdos et al., 2010). Figure 1.2 shows the different factors associated with formation control and cooperative motion planning of a multi vehicle system and factors shared by these two approaches in the design of algorithms.

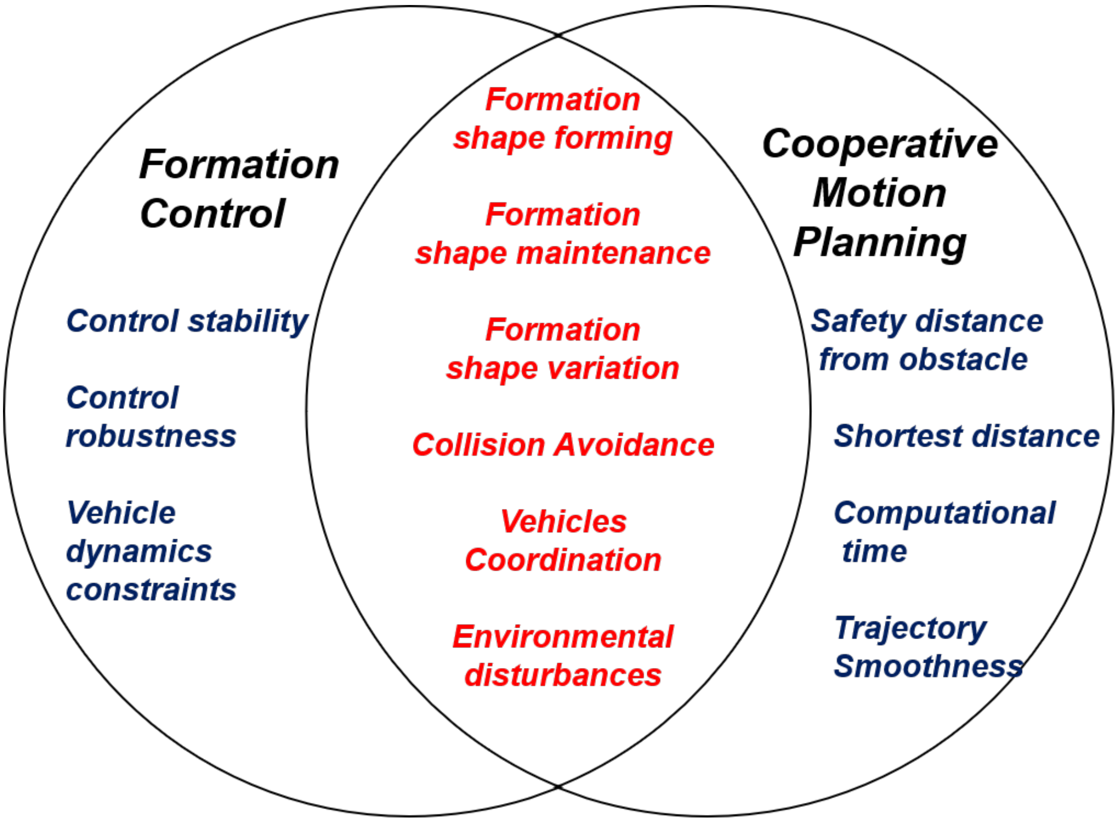


Figure 1.2: Factors associated with formation control and cooperative motion planning (Source: Modified from (Liu and Bucknall, 2018b))

From Figure 1.2, it is evident that formation control and cooperative motion planning shares many key features of a multi vehicle system and should be implemented in an interactive way during the design of algorithms for autonomous operation of a fleet of unmanned vehicles. For example, during motion planning of a multi vehicle system the cooperative motion planning should generate an optimal reference trajectory for these vehicles with least computational effort while the formation control ensuring a stringent following of a reference trajectory with sufficient room for modification in case of collision.

In terms of motion planning of multiple autonomous marine craft on which this current study is focused, it should be noted that there is a much needed requirement of developing a hybrid framework for a multi vehicle system by combining the key factors of the formation control and cooperative motion planning. Until now very few studies have been conducted in the area of marine vehicles to understand the implications of multi vehicle approaches to USVs.

1.1.2 Aim and objectives of this research

As mentioned in Section 1.1.1, this doctoral thesis has the aim of proposing a novel hybrid framework for a multi-USV system by combining the key features of formation control and cooperative motion planning in a practical maritime environment. The research employs the combined use of a constrained A* approach, virtual target approach and swarm aggregation approach towards development of a robust and novel collective framework for multi-USV navigation.

Broken down as sub modules, the specific objectives of this research work are as follows:

1. Critical review of optimal path planning and cooperative motion planning techniques for USVs.
2. Performing a quantitative comparison of a well known heuristic Dijkstra approach against the well known global approach of Artificial Potential Field towards path planning of a USV in a practical maritime environment .
3. To improve the computational efficiency of the conventional A* approach by introducing a constraint of safety distance from the obstacle within the algorithm and proposing a novel, optimal and computationally efficient path planner towards navigation of an USV in a practical maritime environment.
4. To develop a two layered architecture for multi-USV navigation in a practical maritime environment by combining the optimal and computationally efficient path planner with a virtual target based path following approach and swarm aggregation approach based on artificial potential field (APF) method.

Dissemination of the acquired knowledge through publications,including the writing of this thesis, also forms part of the objectives.

1.2 Contributions

This research makes contributions to the existing and available knowledge in the following ways:

1. The current research makes an important quantitative comparison between a well known local approach namely the APF methodology and a well known global approach namely the Dijkstra algorithm towards understanding the effectiveness of path planners in a practical maritime environment. Till now no such comparative study has been conducted in the area of USV navigation in published literature.
2. A novel path planner has been designed for the navigation of a USV in a practical maritime environment based on the conventional A* algorithm. A safety distance constraint has been incorporated into the algorithm and a computationally effective approach is proposed. Previously no such study in USV path planning has been conducted by considering the constraint of safety distance from the obstacle.
3. The novel path planner has been tested in different environmental conditions of moving obstacle and sea surface currents and found to be computationally effective in determining optimal paths. To the best of the author's knowledge, to date no such extensive study has been conducted in USV path planning through heuristic approach by considering environmental conditions and moving obstacle in practical maritime environment.
4. The optimal path planner is integrated with a virtual target based path following technique and a potential theory based swarm aggregation algorithm to develop an integrated framework of multi USV navigation in a maritime environment. It is considered until now no such integrated framework has been studied towards navigation of a multi-USV system.
5. This integrated framework is then modified to avoid the external collision with the shoreline by considering the shore profile as a set of repulsive fixed points which, within a certain distance, concurring in the vehicle motion evolution. Such modelling of a shoreline is another exclusive contribution to the current state of multi USV navigation in a maritime environment.

Each of the above mentioned contributions are verified and added in the current state of approaches adopted in the USV path planning and multi USV motion planning through publications which are mentioned in the next section.

1.3 Outline of the thesis

Following on from this introductory chapter, Chapter 2 summarises and systematically survey the current methodologies adopted for optimal path planning of single unmanned surface vehicles and swarm of USVs and their respective advantages and disadvantages. The literature review is divided into four sections.The first section gives an introduction to the topic. The section after the introductory material comprises of the compilation of notable developments towards optimal path planning of USVs. Next consideration is given to the review of studies towards the operation of multiple USVs in a marine environment. Within the third section, the challenges and scope towards future study in the area of navigation of multiple USVs is considered. Conclusions of the review study are explained in the final section.

Chapter 3 gives an overview concerning the path planning of a single USV using local and global path planning approaches. This chapter deals with explaining the merits of heuristic algorithms over reactive path planning approaches in terms of optimising computational time and path length. The chapter is composed of three sections namely, global approach to path planning of single USV, local approach to path planning of single USV followed by concluding remarks relating to the merits of using an deliberative technique over a reactive one in path planning of marine vehicles in a practical marine environment.

Chapter 4 addresses another practical question and that is, benchmarking and proposing a novel path planner over the ones used till now in the literature in terms of computational time and path length for USV path planning. This study sets up the computational supremacy of the chosen algorithm over the existing ones used in literature in path planning of USV and proposes a new A* algorithm constrained by safety distance from the obstacle. The proposed path planner is tested in different environmental conditions and found to be computationally effective and robust in USV path planning

Chapter 5 then extends the problem of path planning from single USV to multiple USVs by combing the constrained A* path planner with a virtual target based path follower and potential field based swarm aggregation approach towards developing a two layered cooperative framework for multi USV navigation in practical marine environment. This study is the core of the current thesis and is found to be extremely effective in taking into account the different characteristics of single and multi USV navigation of formation control and cooperative motion planning.

The final chapter discusses the research outcomes, draws conclusions and provides suggestions for further work.

Chapter 2

Literature Review

"You do not see there a wireless torpedo; you see there the first of a race of robots, mechanical men which will do the laborious work of the human race"

Nikola Tesla

This chapter summarises current methodologies adopted for optimal path planning of single USV and studies associated with swarm of USVs. The chapter also discusses the challenges and scopes, which can act as objectives, for future research towards path planning of such marine craft.

2.1 Introduction

Marine vehicles can be broadly classified as shown in Figure 2.1. This classification is based on the displaced volume of the vehicles. Each class of vehicle require different autonomy due to the diverse nature of their missions and uncertainties involved in their operational environments. Trans-oceanic voyages of ships, as well as, mission-oriented short time voyages of USVs encounter various obstacles and uncertain environments. Research and development in areas of artificial intelligence, advanced smart sensors, wireless networks and optimisation techniques provide larger scope for contribution in areas of maritime technology(Corfield and Young (2006),Campbell et al. (2012)). The chapter has been organised in ten sections. The second section after the introductory material comprises of the compilation of notable developments towards optimal path planning of USVs. Next, consideration is given to the review of studies towards operation of multiple USVs in a marine environment. Within the penultimate section, the challenges and scope towards future study in the area of path planning of USVs is considered. Conclusions of the review study are explained in the final section.

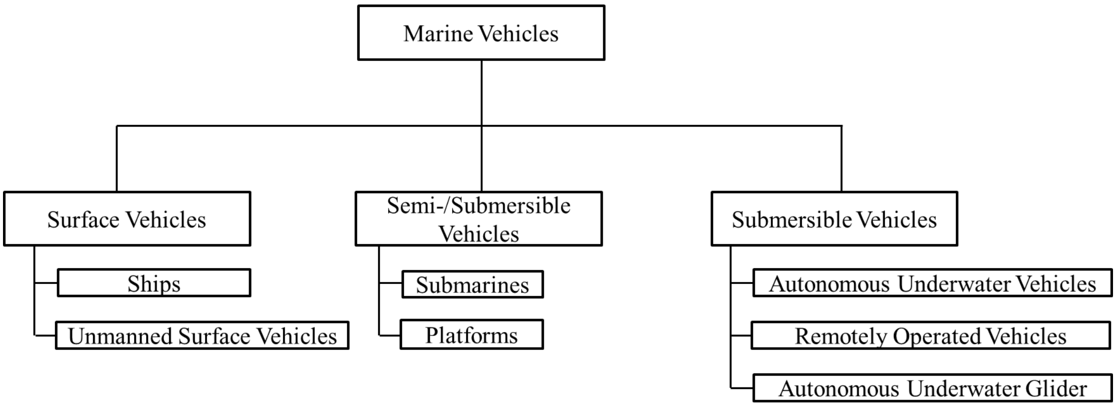


FIGURE 2.1: Classification of marine vehicles
(Source : El-Hawary (2008))

2.2 Classification and architecture of USVs

USVs are watercraft of small (<1 tonnes) or medium (100 tonnes) size in terms of water displacement. The technology of USVs dates back to World War II, but major efforts towards development and understanding the technology started in the 1990s after the successful implementation of USVs in the 1990-1991 Gulf war (Larson et al. (2006)). The basic purposes of USVs are military, surveillance, environmental monitoring, ocean and scientific research and exploration of hydrocarbons.

Classification and developments of USVs based on their application has been explained by Motwani (2012) and shown in Figure 2.2. A few USV prototypes are shown in Figure 2.3.

The general architecture of USV operation in maritime environment has three basic systems namely, control and path planning, communication and monitoring and obstacle detection and avoidance (ODA), which are responsible for mission planning and execution as shown in Figure 2.4. The present policies and law do not allow operation of USVs in maritime environment with the risk of injury and property damage (Zhuang et al. (2011)). This leads to the requirement of development of path planning techniques in compliance with International Regulations for Avoiding Collisions at Sea (COLREGs). Owing to the technical similarities in UGVs and USVs i.e. similar degree of freedom, similar uncertain environment etc. compared to UAVs, path planning techniques can be extended from mobile robots to surface vehicles.

2.3 Environmental mapping

In order to implement the path planning techniques, mapping the environment becomes the initial step. Environment mapping can be qualitative or quantitative and converts world space into configuration or Cspace (Lozano-Perez (1983)). The reduction of a physical space in Cspace helps in quick implementation of algorithms and manageable

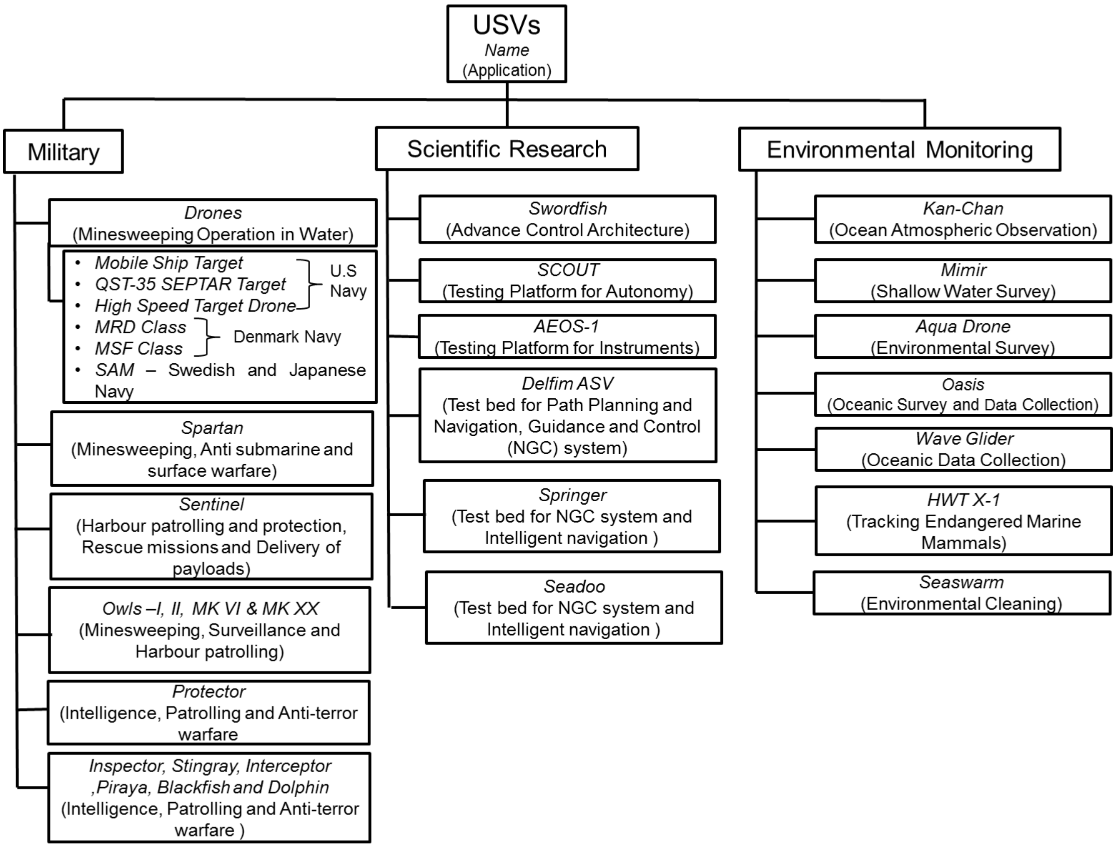


FIGURE 2.2: Classification of USVs based on application; Name (Application) (Source : Motwani (2012))

storage in computers. The Cspace for marine vehicles are dynamic in nature and are highly variable, spatially as well as temporally. The effect of current, winds, tides, etc. needs to be incorporated into mapping so that a robust virtual real-time environment in a simulation can be generated. Qualitative mapping comprises of nodes and arcs, with vertices representing features or landmarks while quantitative mapping comprises of data structures based on way -points or sub-goals (Campbell et al. (2012)). Qualitative and quantitative form of spatial representation is shown in Figure 2.5. The abstraction of path planning is shown in Figure 1.2 .

Qualitative representation expresses space in terms of connections between landmarks and is dependent upon the perspective of a robot while quantitative representation expresses space in terms of physical distances of travel and present a birds eye view of the world. Quantitative representation can be used to generate qualitative representation and is independent of orientation and position of the robot.

Popular mapping techniques are meadow maps, Voronoi diagrams, regular occupancy grid and quadtree mapping (Mooney, 2009) and are shown in Figure 2.6 which are grid-based or metric techniques on which heuristic and evolutionary optimisation methods can be applied effectively.

These mapping techniques transform space into a physical space having co-existence of a robot and obstacles. Meadows map transform the space into convex polygons, which

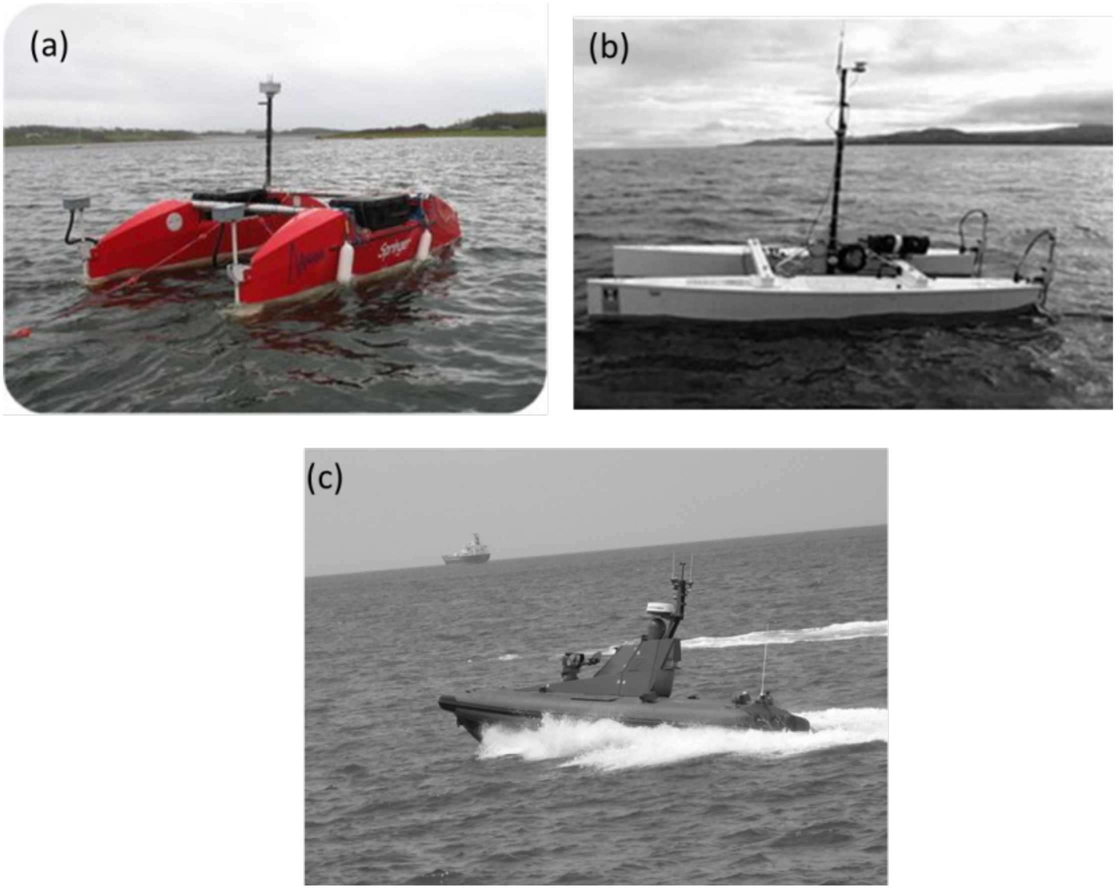


Figure 2.3: A few USV prototypes: (a) *Springer* (Source : Naeem et al. (2007)); (b) *Delfim* (Source : Alves et al. (2006)); (c) *Protector* (Source : Caccia et al. (2008))

represent safe regions for a robot to traverse, and involves selection of best polygons to transit. The midpoints marked on convex polygons become graph nodes for the path planner. Voronoi diagrams are a popular mechanism for representing Cspace and are constructed through generation of Voronoi edges equidistant from the two nearest untraversable points, and their meeting point is called a vertex. The vehicle follows Voronoi edges to avoid a collision. Regular occupancy grids are generated through superimposition of a 2D Cartesian grid on the Cspace. The centre of each element in the grid becomes a node leading to a highly connected graph. Owing to high storage cost of regular occupancy grid, in quadtree mapping, Cspace is represented with a large 2D grid size with grids, in which the vehicle moves, is subdivided into smaller grids. A detailed explanation can be found in Mooney (2009). Higher computational requirement is a major drawback of such techniques against local path planning techniques (explained in Section 2.4). This requirement increases with the representation of the environment with finer grids. Incomplete representation of various real time maritime environments is a major deficiency with these algorithms. Most path planning studies in USVs are restricted with validation of path planning algorithms in such a self-generated environment than in real time environment(Liu and Bucknall (2015)). A novel study by Gadre et al. (2012) proposed a method to generate topological maps of the natural environment for path planning algorithms to generate dynamically feasible trajectories in a short time. This method of generating an environment is still not tested in motion planning of USVs and

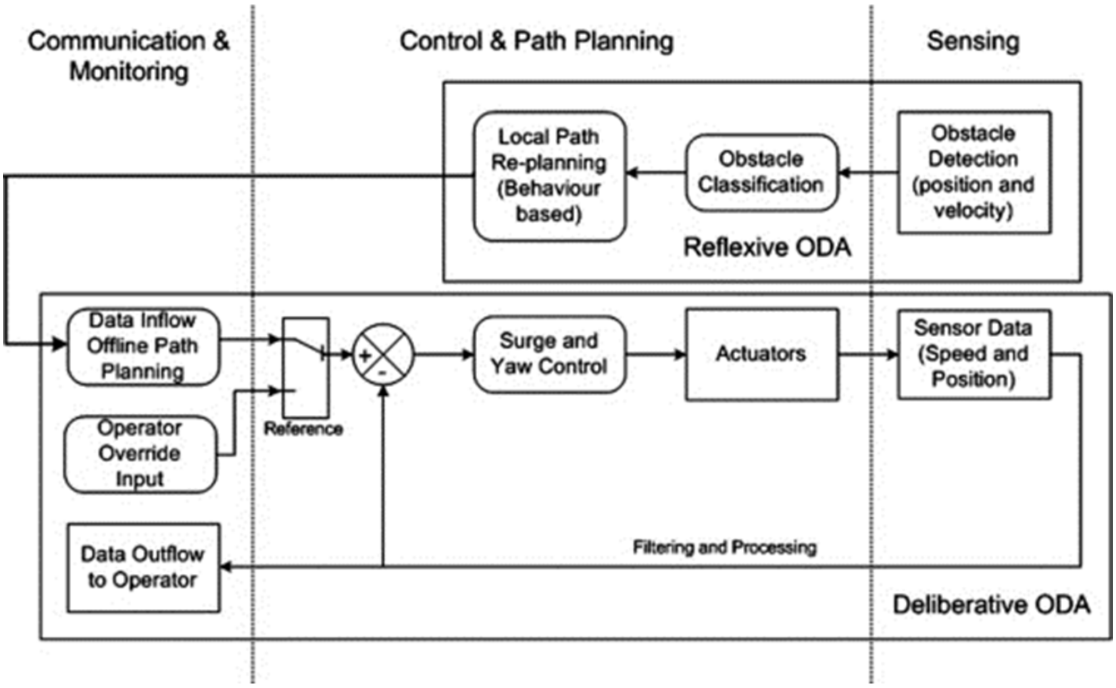


FIGURE 2.4: General architecture of USV (Source : Campbell et al. (2012))

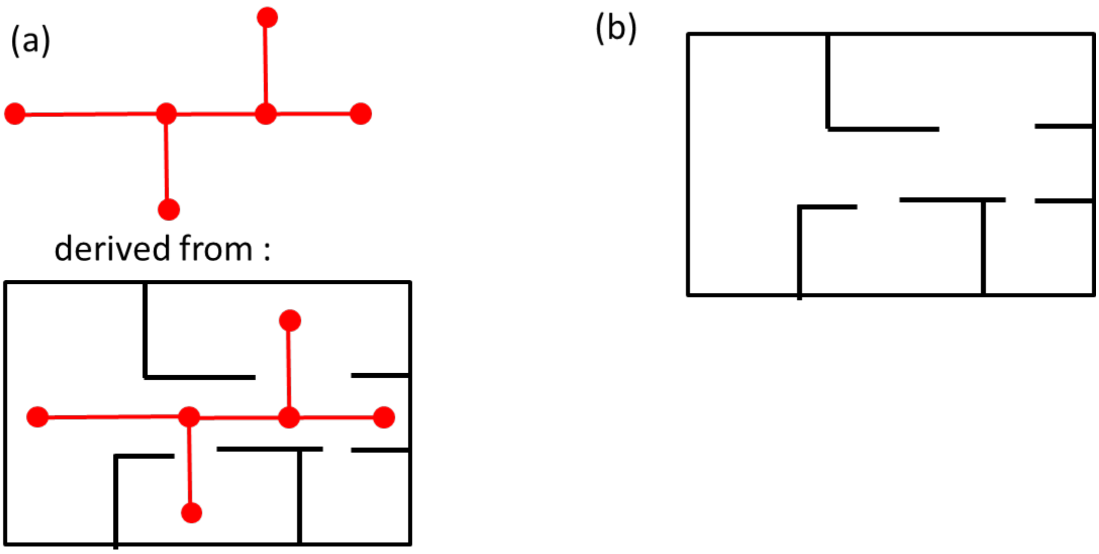


FIGURE 2.5: (a) Qualitative and (b) Quantitative representation (Source : Raja and Pugazhenthi (2012))

provides an exciting prospect towards more realistic simulations for path planning.

In order to generate a map of a real-time environment, simultaneous localisation and mapping (SLAM) is adopted, and which becomes the basis for path planning techniques. A sensor provides topographical data of the region where the vehicle is operating and global path planning techniques are applied to find optimal routes. SLAM and path planning are co-requisites towards increasing autonomy and efficiency of USVs operation in the marine environment. A detailed review of SLAM and its various modules for autonomous mobile robots is explained in Dhiman et al. (2012).The feasibility of SLAM in the absence of global positioning system (GPS) based communication for a USV by building and incorporating parametrised map of a bridge pier structure within

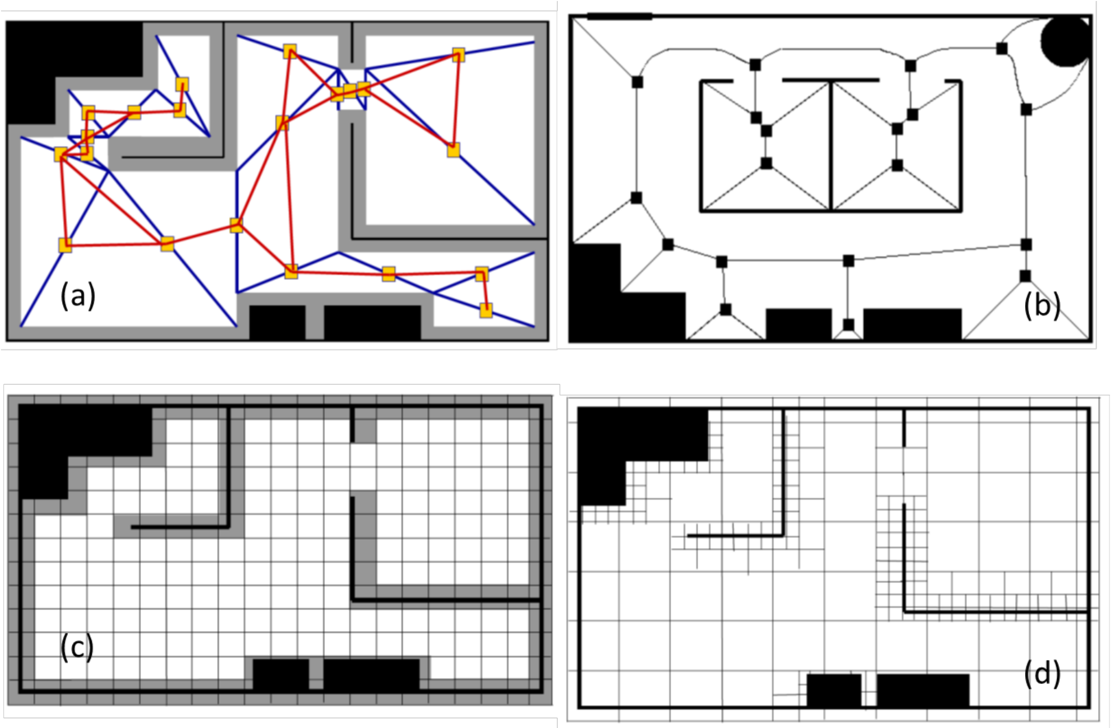


FIGURE 2.6: Grid based environmental mapping : (a) meadow maps; (b) Voronoi diagrams; (c) regular occupancy grid; (d) quadtree mapping (Source : Mooney (2009))

obstacle detection and avoidance algorithm was demonstrated by Han and Kim (2013) and validated with outdoor experiments. In these operations, sensors are prone to noise and errors and there is a requirement of high storage space to collect the continuous data coming from sensors. Along with this, extensive computation is required to process and map the data. Some studies like Park et al. (2008)and Zeng et al. (2009) have adopted a hybrid approach of mixing quantitative and qualitative approaches to counter the extensive data and noise from sensors(Campbell et al. (2012)).

2.4 Global and local path planning

The second stage after mapping the environment is the application of path planning techniques. Path planning techniques for USVs can be divided into local and global approaches. The classification is shown in Figure 2.7.

An offline or global approach is used when complete information of the marine environment is known, while the online or local approach is used when the marine environment changes dynamically during the navigation of marine vehicles. Global approaches comprise of evolutionary and grid based methods. Evolutionary methods are adopted and mimicked from nature, while grid based methods search for optimality within a configuration space. Evolutionary approaches have the advantage of handling multi- objectives in path planning although convergence of such methods is not guaranteed in a finite time and one ends up in a sub-optimal solution. Grid based methods are effective in finding optimal solutions in a configured environment although extensive computation does not

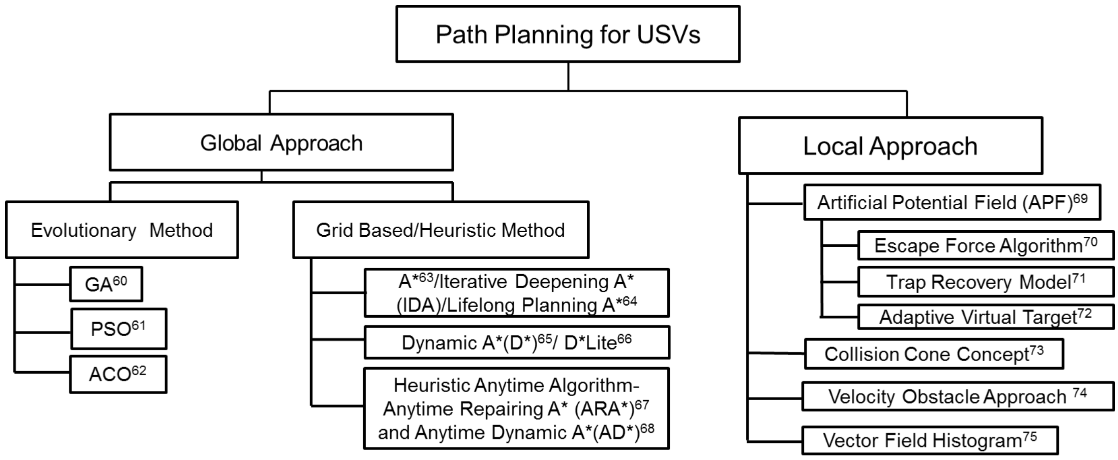


Figure 2.7: Path planning techniques for USV

allow effective real-time implementation in a complex or larger environment, whilst local approaches are suitable for real-time implementation but solutions can get trapped in a local minima.

All path planning techniques are subjected to finding an obstacle free path in a Cspace with certain optimisation objectives. Such objectives vary for single and multiple USVs. Figure 2.8 shows path planning objectives for single and multiple vehicles.

2.5 DOA and ROA based navigation of USVs

Most path planning techniques work in conjugation with a reflexive and deliberative ODA sub system. Most path planning techniques follow way point navigation and are subjected to a DOA and ROA approach to ensure a robust autonomous architecture for an USV operation in real time. DOA refers to far field obstacle avoidance approach where the environment is determined using long range sensors while ROA refers to near field approach where the environment is determined using short range sensors. Most path planning techniques are simulated and tested offline with an assumption that sensors incorporated on an USV for DOA and ROA will provide correct information of the environment during which motion and path planning algorithms will take corrective measures to avoid the collision. . For effective implementation, design of a robust control system is required to follow the generated path. The first real-time implementation of obstacle avoidance using wireless communication in compliance with COLREGs on the SCOUT USV was discussed in Benjamin and Curcio (2004).While Larson et al. (2006) discussed the autonomous navigation and obstacle avoidance approaches and challenges of real time operation with ROA and DOA approaches. The real-time implementation of projected obstacle area method was conducted with the SEADOO Challenger for safe manoeuvring in the presence of obstacles.

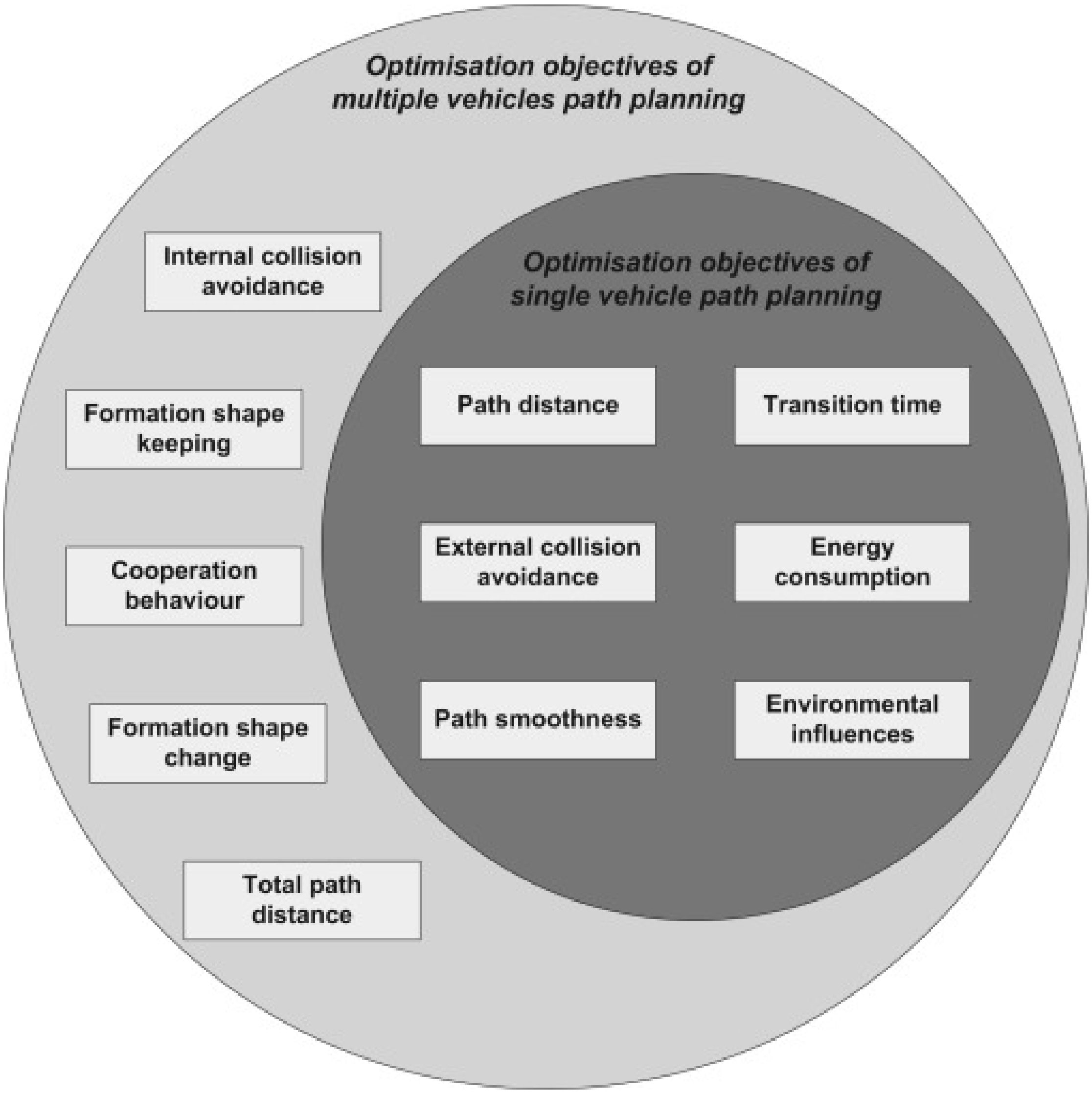


FIGURE 2.8: Comparison of objectives between single and multiple vehicle path planning (Source: Liu and Bucknall (2015))

2.6 Control approaches for USVs

With regards to control techniques for surge and yaw control under control and path planning in 2.4, several methods such as proportional integral derivative (PID) (Caccia et al. (2005)), H∞ (Lefeber et al. (2003)), linear quadratic Gaussian (LQG) (Sharma et al. (2012)), model predictive control (MPC) (Annamalai et al. (2013)) have been proposed. The review of control algorithms and a comparison of linear and non-linear control approaches for USVs can be found in Sharma et al. (2014).Owing to the requirement of offshore industries for underwater inspection and monitoring of offshore establishments, much research towards path planning and control of autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) has been instigated, however, this area is out of the scope of this review. Whereas an extensive review of guidance laws for marine vehicles is discussed in Naeem et al. (2003), a detailed review on developments in areas associated such as path planning guidance with the autonomy of USVs is explained in Campbell et al. (2012).

2.7 Optimal path planning of USVs with time as an objective

To find a feasible path that can be followed in the shortest time is another objective of path planning. Ebken et al. (2005) explained the hardware and software architecture of the SSC San Diego USV and briefly described the path planning approach based on the CMU Morphin algorithm (Bruch et al. (2005)) used for determining the minimal time path during real time testing of the vehicle. Casalino et al. (2009) have proposed a three-layer path planning architecture comprising of DOA and ROA approaches based on a visibility graph technique and a A* algorithm to find a path having minimal time for an USV. Salarieh and Ghorbani (2011) used a Gauss spectral method to determine an optimal trajectory for a high-speed boat using a non-linear mathematical model. This novel approach takes into account the dynamics of the vessel and was found computationally less expensive in terms of storage and time. Svec et al. (2012) developed a moving object following trajectory planning of an USV based on lattice-based trajectory planning to generate a dynamically feasible and optimal path and verified the simulation against experiment trails. Recently, evolutionary approaches have been brought in to the path planning of USVs. Song (2014) proposed an improved ant colony algorithm (ACO) for a global path planning algorithm of a USV. The proposed approach needs less computational time and produces a smooth path. Furthermore, Song et al. (2015) proposed a modified particle swarm algorithm (PSO) algorithm based on a particle model for obstacle avoidance and compared results against path generated using a conventional PSO and smooth path planning algorithms. The proposed algorithm produced a shorter and smoother path against a conventional PSO and smooth path planning algorithms. In order to combine the advantages of the global and local path planning algorithms, a combinatorial approach has been proposed using an angle potential field and a modified ACO by Wu et al. (2015). This approach provides an optimal result in terms of path length.

Recently, a number of studies have forthcoming in the area of path planning of USVs which need to be acknowledged here. Wang et al. (2018a) proposed a A* method with post smoothing for USV navigation in a real navigation map. Wang et al. (2018b) also made a study towards development of a global path planning system for USV navigation. Liu et al. (2015) used a novel FM method for USV navigation in a practical maritime environment. Another important extension of the same study where an improved FM method was used for USV navigation is proposed by Liu et al. (2017a). In order to incorporate the dynamic characteristics of the moving vessel within the FM method, a novel approach is proposed is proposed by Liu et al. (2017b).

In addition, two important dissertation works need a special mention. Shah (2016) has proposed an improved A* method in a PhD study for USV navigation in an environment comprising of static and dynamic obstacles. The work also considers the effect of environmental disturbances. Whilst, Schnieders (2018) also attempted to experimentally verify the effectiveness of APF method in a real navigation map. The approach uses a combined use of MATLAB and Gazebo simulation on the *Clearpath* USV.

2.8 Path planning of a swarm of USVs

Swarm is defined as multiple autonomous agents moving cooperatively to fulfil global objective of a scientific or technological mission. This term is often observed in nature. Each autonomous agent is modelled as a particle and characterised by its position and a function describing its dynamics. The cooperative behaviour of swarm of vehicles can be classified into two categories: (a) formation control and (b) cooperative motion planning. Extensive research has been conducted to understand the cooperative behaviour of swarm of UAVs and UGVs operating in static and dynamic environments.

Literature pertaining to swarm of UAVs and UGVs shows that formation control follows four approaches namely, leader-follower (Das et al. (2002)), behaviour based approach (Balch and Arkin (1998)), virtual structure (Ren and Beard (2004)) and artificial potential function (Bennet et al. (2011)). In the leader-follower approach, one vehicle acts as a leader and generates the reference trajectory for other vehicles. The behaviour of the leader decides the behaviour of the swarm. In the behaviour based approach, the behaviour is decided on weighted average of individual actions of each vehicle, where actions can be formation keeping, obstacle avoidance etc. In the virtual structure approach, the complete swarm formation is considered as a rigid body and the dynamics of each agent is derived from the dynamics of a rigid body. This flexible approach can accommodate all forms of formation and is a decentralized behaviour. Finally, the artificial potential function approach to control the swarm geometry and inter-member spacing through vector fields created by repulsive and attractive potential fields. Path planning approaches have already been discussed in detail in the previous section which can be coupled with formation control approaches for motion planning of swarm of vehicles. A detailed review of literature towards cooperative path planning of aerial and mobile robots can be found in the work of Wang and Phillips (2014).A broad description of survey towards formation control and cooperative motion planning has been made in the chapter 5.

A swarm of USVs in an oceanic environment is another major challenge for better temporal and spatial coverage of the oceanic environment. A swarm of USVs is a multi-objective problem where the vehicles have to find an obstacle-free path while maintaining the shape of the fleet of USVs to the maximum extent. Objectives associated with multiple USVs path planning can be found in Figure 2.8. There are basically three control structures to maintain the shape of USV fleets, namely, leader-follower, virtual structure and behaviour based approach (Liu and Bucknall (2015)). A detailed review towards multi-robot coordination can be found in Yan et al. (2013). Heuristic approaches have been found better in dealing with such multi-objective problems. The next important consideration is the selection of formation shape for the fleet. Line, column, diamond and wedge shapes are the most popular geometric patterns(Campbell et al. (2012)). Very few studies have been commenced towards the development of a robust path planning algorithm for a swarm of USVs. Bishop (2004) demonstrated real-time planning and control architecture for a platoon of USVs. Schneider et al. (2008) proposed a Kalman filter based navigation for three unmanned marine vehicles with narrow bandwidth communication moving in a wedge-shaped formation whereas Frey et al. (2008) explained navigation of a swarm of USVs based on the basic law of physics. This decentralised approach demonstrated a reduction in energy consumption by use of a short range self-contained processing unit than a leader one. Abidin et al. (2011) proposed a fly optimisation algorithm (FAO) for a swarm of mini USVs in the range of 8 to 24 vehicles. Recent work of Liu and Bucknall (2015) successfully demonstrated implementation of a path planning method based on the fast marching (FM) approach for USVs as a fleet of vehicles in a dynamic environment for various scenarios. Liu and Bucknall (2016a) proposed an effective path planning algorithm for multi USV formation by incorporating heading angle into a FM method. This approach produces paths which are in compliance with the heading angle of the USV. Cao and Chen (2018) proposed another method novel method for multi USV navigation based on an artificial bee colony algorithm.

2.8.1 Challenges and scope for the future

A review of path planning of USVs shows that other than the work of Wu et al. (2015), no attempt has been made towards the development of hybrid algorithms to obtain global optimality without getting trapped in local minima. Most of the studies have been simulated in the self-generated environment and there is a need to simulate path planning algorithms in maps generated from the real-time environment. Other than work of Gadre et al. (2012) and Liu and Bucknall (2015), no other work has made an attempt towards this. In order to implement algorithms in real time, there is a need to develop algorithms which are computationally less demanding. Only the work of Larson et al. (2006), Benjamin et al. (2006) and Svec et al. (2012) have made attempts towards real-time implementation of such algorithms. Swarm operations of USVs is still an open area where not many developments have occurred and understanding the dynamics of the fleet of USV in compliance with the hybrid framework comprising of characteristics of formation control and cooperative motion planning needs to be studied. Most studies with USV path planning assume dynamic obstacles and USV at a constant speed. There is a requirement to develop an integrated framework which can incorporate dynamics of USV in cooperative motion planning of USVs with least computational effort.

2.9 Conclusions

This chapter systematically surveyed the optimal path planning approaches adopted for single and swarm of USVs and their respective advantages and drawbacks. Initially, optimal path planning approaches currently adopted in the literature for single USVs is analysed with ROA, DOA and SLAM techniques in two respects, static and dynamic environment. This is followed by path planning approaches adopted for a swarm of USVs. Finally, on basis of the investigation of the related literature, challenges and prospects for future research avenues with single and multiple USVs has been presented.

On the basis of the review of the literature pertaining to the path planning of single and swarm of USVs, it is established that there is a requirement of wide research in this area. Initially, there is a need to benchmark heuristic approaches against local approaches for USV path planning quantitatively in terms of computationally effectiveness in practical maritime environment. There is also a strong need to develop new heuristic algorithms which are computationally efficient and provide safer paths for the USV navigation and the current thesis makes an novel effort in this direction through the development of a path planner that takes into the account of environmental uncertainty of the maritime environment .Towards the multi-USV system, there is a need to integrate path planing, path following and swarm approaches together to develop a novel integrated framework applicable in the practical maritime environment and takes into account the characteristics of the formation control and cooperative motion planning as shown in Figure 1.2. The upcoming chapters deals with all these objectives of the USV path planning and multi USV system towards the development of a hybrid cooperative framework for the swarm of USVs.

The present chapter has been published as a review study by the Indian Journal of Geo-Marine Sciences (IJGMS) which is added in Appendix B.

Chapter 3

Heuristic versus Local Approaches

"If you're not benchmarking your performance against your competitors, you're just playing with yourself"

Al Paison

The present chapter presents a quantitative comparison of a well known heuristic approach namely Dijkstra against a another well known local path planning approach APF towards path planning of a USV in a practical maritime environment. This study compare the effectiveness of the two well known path planning approaches in terms of computational time. The major aim of the current chapter is to benchmark quantitatively the computational performance of heuristic approaches against the local approaches in the USV path planning.

3.1 Introduction

Advanced electronic navigation has become an irreplaceable guide to navigate USVs intelligently along shorelines and docks. Path planners always work in a discreet workspace to find solutions. Two major approaches are studied in robotics towards this namely, heuristic and local approaches as explained in Chapter 2. Within local approaches, APF is a well-known approach which has been extensively used in the literature towards path planning of mobile and aerial robots while within the heuristic approaches, Dijkstra was the first method adopted in mobile and aerial robotics for path planning. Although a huge number of benchmark studies have been conducted in mobile and aerial robots, these approaches have not been benchmarked in a configuration space of a practical maritime environment for USVs. Towards specifying a quantitative figure and to establish the supremacy of heuristic approach in terms of cost and implementation in a practical maritime environment, two of the most popular approaches have been adopted in this chapter.The main scholarly effort of this chapter is towards providing a basic overview of the path planning approaches leading to the development of a reliable path planner in the coming chapters.

Many advanced path planners have been developed over the last few decades and few of the most popular ones are A*, D* and Rapidly-Exploring Random Trees (RRT) to name a few. These advanced versions have been developed for solutions towards a specific requirement within the robotic path planning. In the current thesis, a modified version of A* has been implemented in the subsequent chapter as a novel method and has been benchmarked. Unlike A*, D* is an expensive approach as the dimension of the search space increases and has to re-plan the path with increasing search space. RRT is a sampling based method with high computational cost involved for finding path. Also there is a need to add additional algorithms with RRT to define optimality for path planning. Hence in terms of optimality and easier implementation, Dijkstra and APF were chosen towards the benchmark study.

The chapter is organised in four sections in which the next section after this introduction discusses the results associated with path planning of USV using a well known local approach, APF and various drawbacks associated with the local approach. Section three deals with the application of a well known optimal algorithm, Dijkstra, in path planning of an USV. The final section deals with discussion related to application of local and global approaches for real time implementation in a practical marine environment.

3.2 Path planning of an USV based on APF

In robotics, various local approaches such as Collision Cone Concept (Chakravarthy and Ghose (1998)), Velocity Obstacle Approach (Fiorini and Shiller (1998)), Vector Field Histogram (Borenstein and Koren (1991)) and APF (Khatib (1986)) have been proposed in the literature. Since most of the robotics problems is real time, the need to have a very fast and simple motion planner is evident. The simplicity enables fast development and deployment of a robot, whereas the computationally inexpensive nature allows the algorithm to be implemented with minimum sensing capabilities. APF is one of the simplest local methods, and the method is capable of autonomously moving a robot in a realistic obstacle framework with real time implementation. In the present study, an effort in the direction to understand the effectiveness of APF in path planning of an USV in a practical marine environment has been made.

3.2.1 APF : Concept and methodology

APF solves the path planning problem by assuming all obstacles are a source of repulsive potential, with the potential inversely proportional to the distance of a robot from the obstacle while the goal attracts it by applying an attractive potential (Kala (2016)). The derivative of the potential gives the value of the virtual force applied on the robot, which moves the robot from start to goal point(Kala (2016)). The motion is completely local in nature. A schematic of the APF is shown in Figure 3.1.

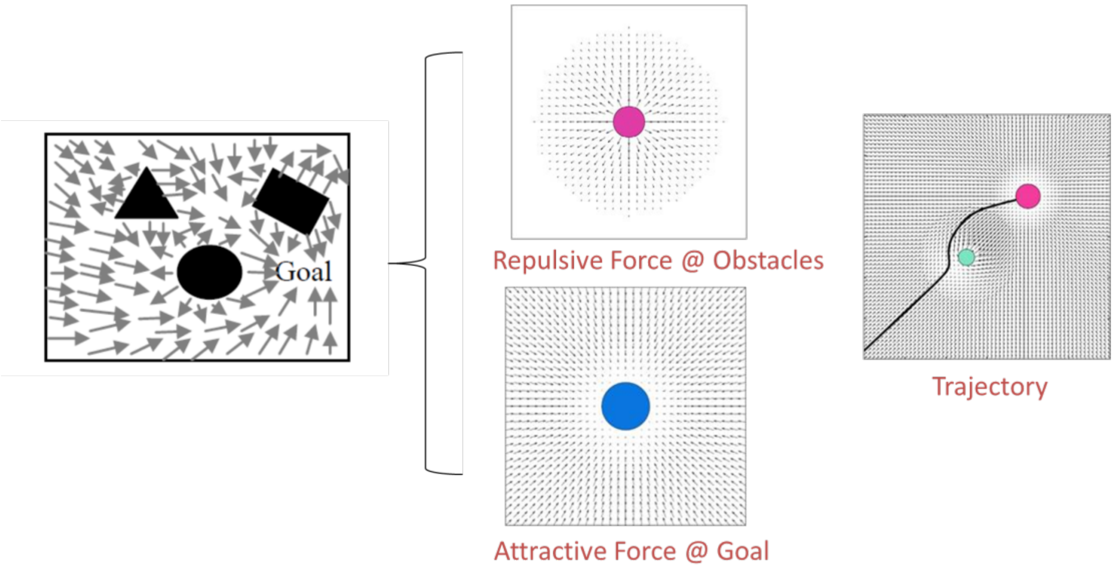


FIGURE 3.1: Schematic of the APF. In the path planning of a robot, potentials are expressed in the workspace of the robot. Obstacles which have to be avoided are surrounded by repulsive potential fields and the goal point is surrounded by an attractive field. These potentials are added to form a composite potential as shown in the figure on the most left hand side of the schematic. The robot moves in this field as shown in the trajectory

3.2.2 Attractive Potential

The attractive potential is applied by single goal to direct a robot towards itself. The attractive potential is directly proportional to the distance between the current position of the robot and the goal. This causes the potential to tend to zero as it approaches the goal and hence slows down as it approaches the goal (Kala (2016)). The potential in this study is taken as, a quadratic potential, as represented in Eq. 3.1.

$$U_{att}(x) = \frac{1}{2} K_{att} \|x - G\|^2 \tag{3.1}$$

where, x is the current position of the robot and G is the goal. $\|.\|$ is the Euclidean distance function and K_{att} is the proportionality constant, where the degree is taken as two.The driving force is a vector whose magnitude is measured through the derivative of the potential function and the direction as the line which maximizes the change in potential, which is given by Eq. 3.2.

$$
\begin{aligned}
F_{att}(x) = \nabla U_{att}(x) = K_{att}\|x - G\|.u(x - G) \\
= K_{att}\|x - G\|\frac{(x - G)}{\|x - G\|} \\
= K_{att}(x - G)
\end{aligned}
\tag{3.2}
$$

where, $u()$ is the unit vector

3.2.3 Repulsive Potential

The repulsive potential is applied by obstacles which repel a robot coming close and repelling it to avoid a collision. The potential is inversely proportional to the distance so that potential tends to infinity if the robot comes near an obstacle leading to repulsion. Obstacles at a certain distance d^* are considered in modelling the potential (Kala (2016)).

The repulsive potential is given by Eq. 3.3

$$
U_{rep}(x) = \begin{cases} \frac{1}{2}K_{rep}\Big(\frac{1}{\|x - o_i\|} - \frac{1}{d^*}\Big), & \text{if } \|x - o_i\| > d^*. \\ 0, & \text{if } \|x - o_i\| < d^*. \end{cases}
\tag{3.3}
$$

where, x is the current distance of the robot and o_i is the position of the obstacle. $\|.\|$ is the Euclidean distance function and K_{rep} is the proportionality constant, where again the degree is taken as two.

The repulsive force is given by Eq. 3.4, which is a derivative of the repulsive potential

$$
\begin{aligned}
F_{rep}(x) = \nabla U_{rep}(x) = -K_{rep}\Big(\frac{1}{\|x - o_i\|} - \frac{1}{d^*}\Big)\frac{1}{\|x - o_i\|^2}u(x - o_i) \\
= -K_{rep}\Big(\frac{1}{\|x - o_i\|} - \frac{1}{d^*}\Big)\frac{1}{\|x - o_i\|^2}\frac{(x - o_i)}{\|x - o_i\|} \\
= -K_{rep}\Big(\frac{1}{\|x - o_i\|} - \frac{1}{d^*}\Big)\frac{(x - o_i)}{\|x - o_i\|^3}
\end{aligned}
\tag{3.4}
$$

where, $u()$ is the unit vector

3.2.4 Resultant Potential

The resultant potential is given by sum of attractive and repulsive potential. This final force is henceforth, the derivative of the resultant potential. This is given in Eq. 3.5.

$$
\begin{aligned}
U &= U_{att} + U_{rep} \\
F = \nabla U &= \nabla U_{att} + \nabla U_{rep} = F_{att} + F_{rep}
\end{aligned}
\tag{3.5}
$$

3.2.5 Methodology

In the present study, a realistic marine environment i.e. Portsmouth harbour has been chosen as the area of navigation. Portsmouth has been chosen towards simulation study due to its economic significance. A start point and goal point as shown in Figure 3.2 was chosen for an USV to navigate.

FIGURE 3.2: Simulation area- Portsmouth harbour (Source: *Google Maps*)

A binary map of 800x800 pixel grid resolution (shown in Figure 3.3) was taken into account with an USV available at the University of Plymouth named, *Springer*. This being considered in terms of kinematic constraints for the purpose of path planning. In the given simulation, only two parameters from the list of parameters for *Springer*, namely size and speed of the *Springer* has been considered while the other parameters mentioned on Table 3.1 are based on the constraints of the equations of the potential field. In this map, each pixel corresponds to 3.6 m of length on the real map. Parameters used in APF for path planning of *Springer* are shown in Table 3.1. *Springer* is shown in Figure 3.4.

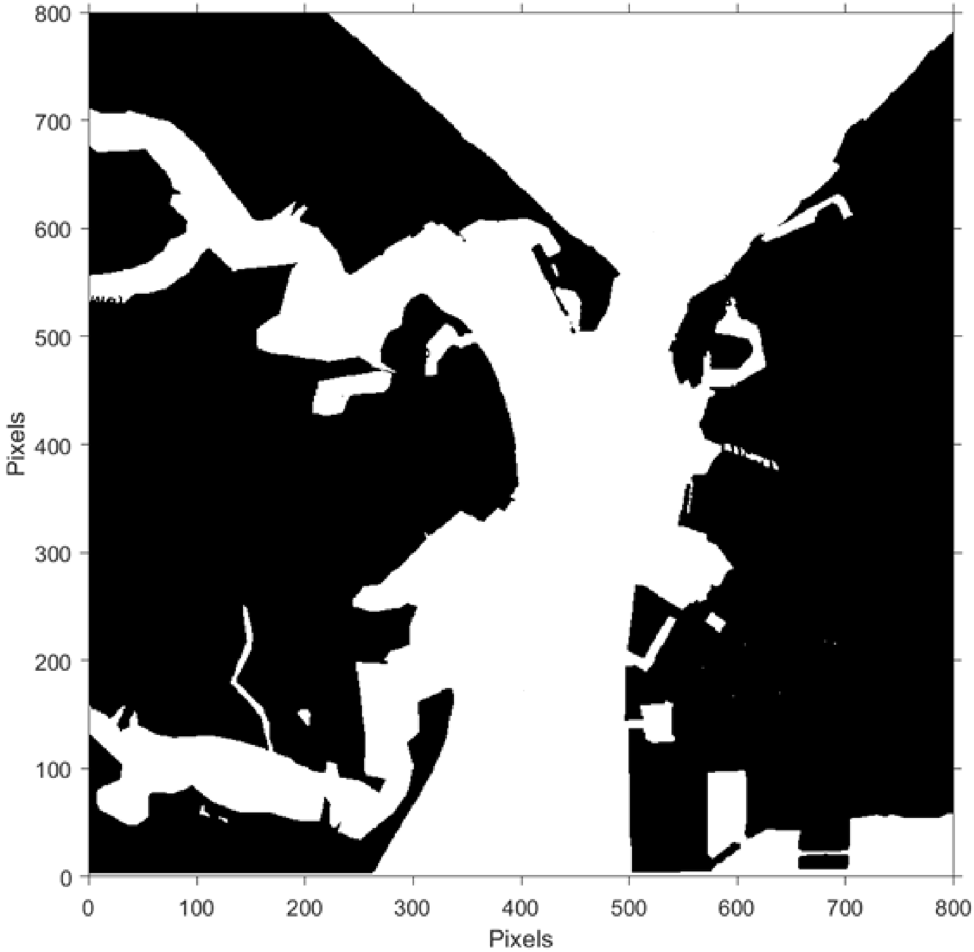


FIGURE 3.3: Binary map of the simulation area

FIGURE 3.4: The *Springer* USV

The algorithm has been coded in MATLAB and simulations run on a computer with a Pentium $i5$ 2.7 GHz processor and 16 GB of RAM

TABLE 3.1: Parameters used in APF for path planning of *Springer*

Parameters	**Values**
K_{att}	300000
K_{rep}	300000
USV Size (*Springer* Size)	4 m (Length); 2.3 m (Width)
USV Speed	4 m/s (maximum speed of *Springer*)
Safety distance from obstacles (d^*)	108 m
Maximum turn rate (deg./s)	10
Initial heading of USV (deg.)	-45°

3.2.6 Results

Evaluation of the APF performance for USV path planning in terms of path length, path cost and computational time is described in Table 3.2. Simulation records movement sequences of the USV within the map. Figure 3.5 shows the sequence of USV motion from start to goal point at different times of the motion. The initial heading of the USV in Figure 3.5 is based on the net potential field created as a summation of the attractive and repulsive fields. The overall trajectory shows that such algorithm is efficient in generating safe path for USV in a practical marine environment.

TABLE 3.2: Performance of APF in *Springer* navigation

Parameters	**Value**
Path Length	3.1 Km
CPU Time	32.61 s

Table 3.2 shows that USV is able to find a safe trajectory of length 3075 m within 32.608 s which means, less than 1 second is required by the USV to find a path of 1m. This leads to the fact that real time implementation of such a algorithm is possible within a practical marine environment. Since the APF is a parameter dependent algorithm, there is a need to find the right set of parameters for different case scenarios.

Although local techniques have dominated the area of robotic path planning before 2000, but owing to their incomplete, non optimal nature with several drawbacks associated, heuristic approaches and their different variants have been in usage in the last two decades (See Figure 3.6). Local techniques no longer provide suitable and effective results for robot navigation in an unknown and dynamic environment compared to heuristic techniques owing to several following drawbacks (Borenstein and Koren (1991)) :

1. Trap situation owing to local minima.

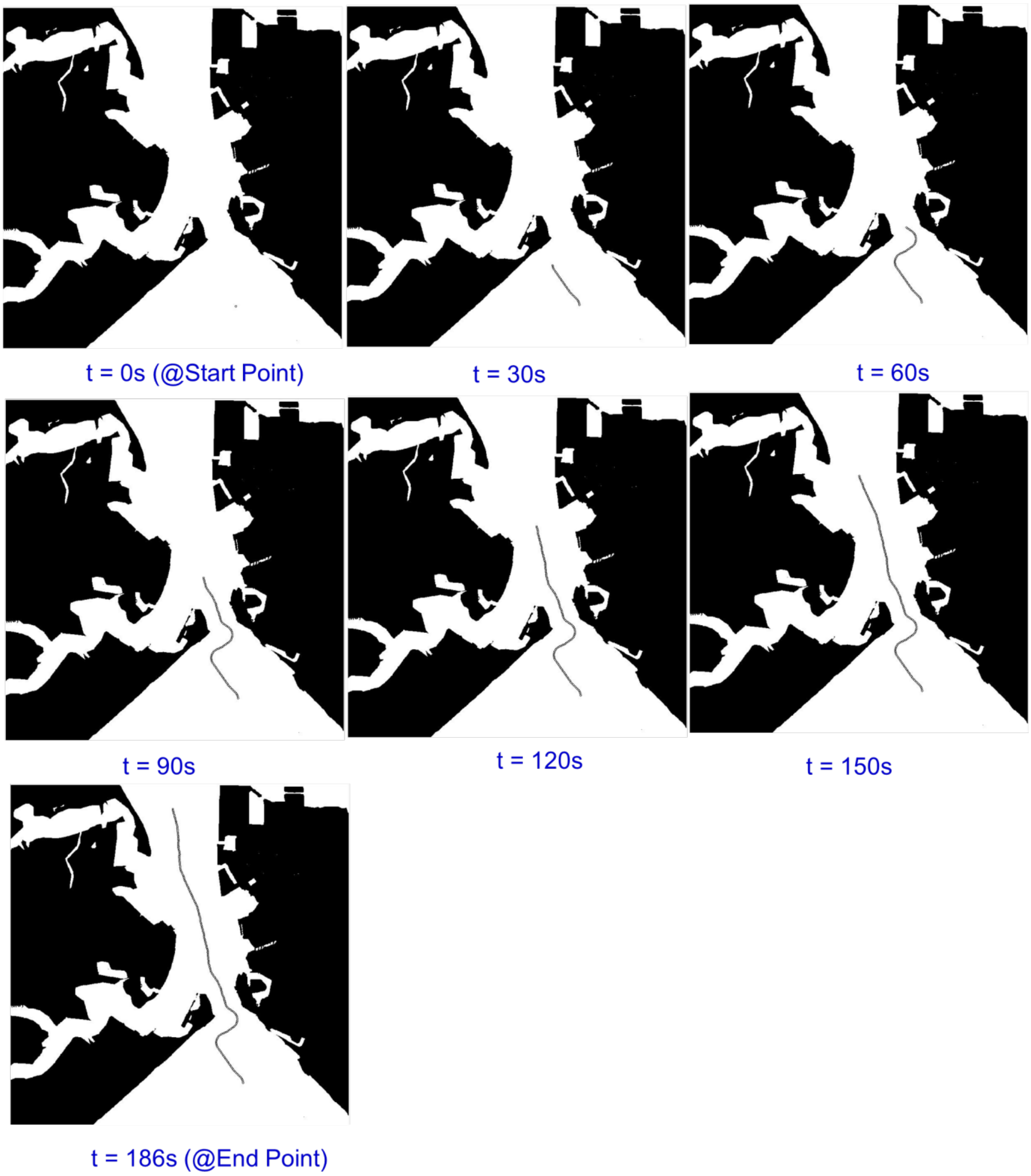


Figure 3.5: Sequence of USV motion from start to end point

2. Inability to find a path between closely spaced obstacles.

3. Oscillations in narrow passages.

4. Goals non reachable with obstacles nearby (GNRON)

Although various studies have been conducted to overcome these drawbacks as suggested by Ge and Cui (2002), Huang (2007), Huang (2009), Valbuena and Tanner (2012) and Hui and Pratihar (2009) using a modified potential field method, computational time, incomplete and non-optimal nature makes use of heuristic algorithms more suitable for online implementation. A simulation study has been conducted in the next section using a well known heuristic approach, namely, the Dijkstra algorithm to understand the effectiveness of the use of heuristic approaches in path planning of a USV in a practical marine environment.

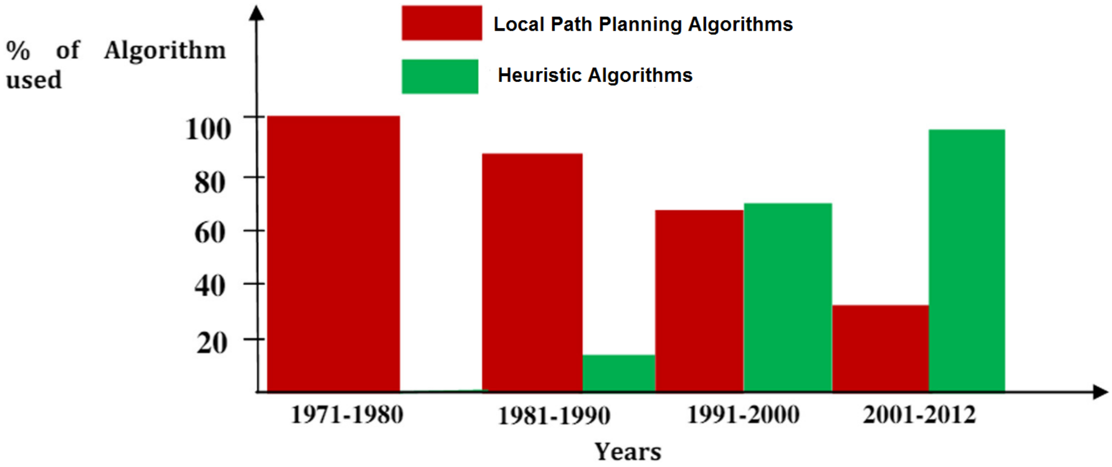


FIGURE 3.6: Application of local and heuristic algorithm (Modified from Source: Mohanty and Parhi (2013))

3.3 Path planning of a USV based on a Dijkstra approach

Under global approaches, grid map based path planning techniques are best known since they generate sub optimal trajectories with a faster computation time. These grid map based approaches follow heuristic, a practical method of finding an optimal solution in an complex scenario to speed up the process of finding an satisfactory solution. Planning consists of finding a sequence of actions that transforms some initial state into some desired goal state. In heuristic path planning, the states are agent locations and transitions between states represent actions the agent can take, each of which has an associated cost. A path is optimal if the sum of its transition costs (edge costs) is minimal across all possible paths leading from the initial position (start state) to the goal position (goal state). A planning algorithm is complete if it will always find a path in finite time when one exists, and responds in the finite time if no path exists. Similarly, a planning algorithm is optimal if it will always find an optimal path.When the dimensionality of the planning problem is low, for example when the agent has only a few degrees of freedom, heuristic algorithms are usually favoured because they provide bounds on the quality of the solution path returned.

Dijkstra (1959) initiated the work in the area of grid map-based path planning algorithms by describing the shortest path between two nodes specified on a map. This was later improved by Hart et al. (1968) who introduced A*, which is an extended version of Dijkstra algorithm. In the last two decade, many variants of A* have been introduced by various researchers to improve the performance of robots working in a number of environments. Stentz (1995) introduced the first major improvement of A*, the focused D* algorithm for real time path replanning which was later improved for a partially unknown environment by the induction of D* Lite (Koenig and Likhachev (2002)). Another improvement by fixing infelicities of A* in a dynamic environment was introduced by Likhachev et al. (2005) through the Anytime Dynamic A*. Since these algorithms do not consider the heading and dynamics of a robot, another major improvement was introduced in the form of the Theta* (Nash and Felner (2007)). This algorithm accounts for the heading angle and yaw rate of a robot in the path planning, which is a necessity for USV path planning since it cannot follow an unrealistic path with sharp turns (Kruger and Briganti (2007), Prasanth-Kumar and Kumar (2005), Yang and Wang (2005)). Advanced approaches like the ant colony algorithm (ACO) (Song (2014)) and particle swarm optimization (PSO) (Song et al. (2015)) have been adopted for USV navigation but cannot generate trajectories in real time due to a high computational load. Along with this, these algorithms do not give consideration to vehicle dynamics and turning radius.

Many studies in marine navigation have been conducted, but most of them have been related to collision avoidance rather than the path planning problem (Tam and Bucknall (2010)). Even studies conducted on optimal USV navigation have been struggling with high computational load and are incapable of generating a trajectory in real time. This study presents the use of the Dijkstra algorithm in a real time environment with minimum computational load to generate a trajectory within a real time operation. This approach is well suited for optimal USV navigation in a static environment with minimum computational requirement.

3.3.1 Methodology : Dijkstra Algorithm

There are various variants of the Dijkstra algorithm. The variant used in this study fixes a source node which is the start point of the USV and finds the shortest paths from source node to all other nodes in the graph leading to shortest- path tree. In order to reduce the computational load in the original variant, a sparse graph i.e. graph with fewer edges approach has been adopted leading to more efficient storage of graph nodes. The algorithm is defined in Table 3.3 (Ahuja (1990)).

TABLE 3.3: Dijkstra Algorithm

Algorithm 1. Dijkstra (Graph, source)

function Dijkstra(Graph, source):
create vertex set Q
for each vertex v in Graph: // *Initialization*
dist[v] ← INFINITY // *Unknown distance from source to v*
prev[v] ← UNDEFINED // *Previous node in optimal path from source*
add v to Q //*All nodes initially in Q (unvisited nodes)*
dist[*source*] ← 0 // *Distance from source to source*
while Q is not empty:
u ← vertex in Q with min dist[u] //*Node with the least distance will be selected first*
remove u from Q
for each neighbour v of u: // *v is still in Q*
alt ← dist[u+ length(u, v)]
if *alt* < dist[v]: // *A shorter path to v has been found*
dist[v] ← *alt*
prev[v] ← u
return dist[], prev[]

In the given algorithm in Table 3.3, the code $u \leftarrow$ vertex in Q with min dist[u] searches for the vertex u in the vertex set Q that has the least dist[u] value. length(u, v) returns the length of the edge joining (i.e. the distance between) the two neighbour nodes u and v. The variable *alt* on line 12 is the length of the path from the root node to the neighbour node v if it were to go through u. If this path is shorter than the current shortest path recorded for v, that current path is replaced with this *alt* path. The *prev* array is populated with a pointer to the "next-hop" node on the source graph to get the shortest route to the source.

In order to use a practical environment, Portsmouth harbour, which was used for the APF in the previous section, has also been considered as shown in Figure 3.2. The map is organised as a weighted occupancy map using a cell decomposition method . This map represents obstacles as black and free space as white in a matrix of black and white as shown in Figure 3.3.The algorithm has been coded in MATLAB and simulations run on a computer with a Pentium $i5$ 2.7 GHz processor and 16 GB of RAM

3.3.2 Results

In this study, computational time of the simulation for three different start and a fixed goal node have been compared in order to determine the effectiveness of the algorithm in term of computational time to find an optimal trajectory in a practical marine environment. Figure 3.7 shows three different start nodes within the grid map having a fixed goal node. These starting nodes are chosen arbitrarily within the grid map on different positions within the simulation area to show the effectiveness of the algorithm in finding different trajectories with least computational load.The simulations are assumed to be used by *Springer*.

Table 3.4 shows the comparison of computational time for three cases as shown in Figure 3.7. The results show that the trajectories generated by the Dijkstra algorithm within a huge grid map from any source nodes satisfy the computational efficiency. All cases are able to generate a complete path in less than 7 seconds which in turns lead to the generation of path in less than 1 second per metre length of the distance covered by USV. Henceforth, such an algorithm is applicable in a real time operation where faster optimal trajectories are needed to be generated. Since the maximum speed of the USV for which the algorithm is designed is 4 m/s, henceforth, the proposed approach satisfies the dynamic constraints of the platform.

3.4 Concluding remarks

This chapter divides the problem of a USV path planning into global and local approaches through simulation studies conducted using two well known methods the Dijkstra and APF respectively. The APF and its respective local approach variants are

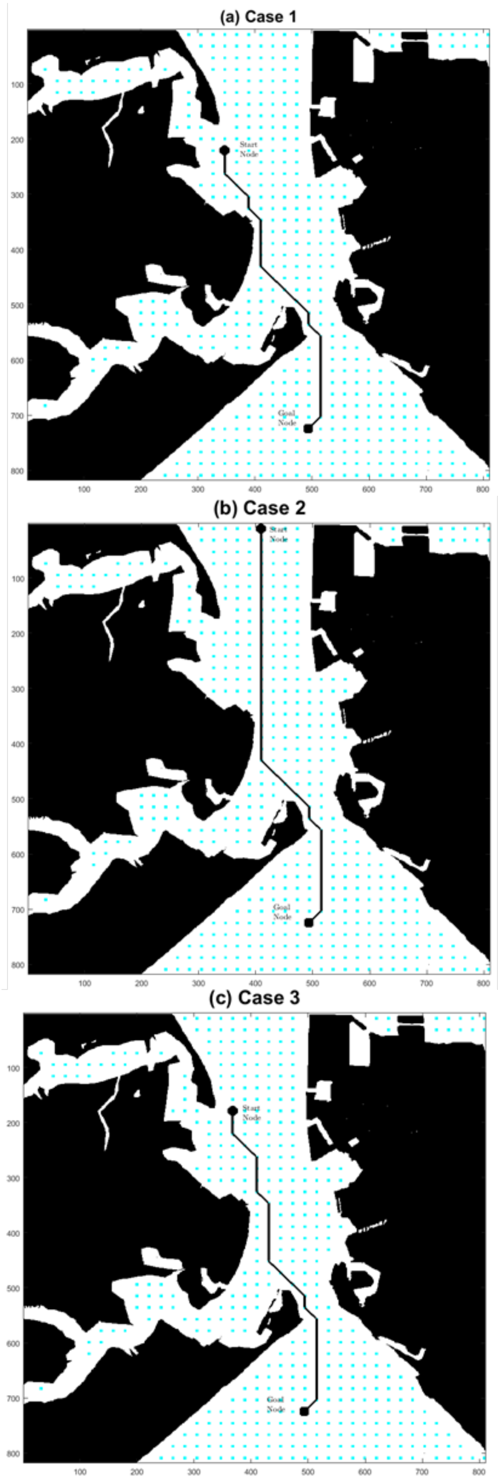


FIGURE 3.7: Simulation results for three cases of the Dijkstra algorithm

easy to implement. A comparative result in terms of the computational performance of these two approaches is summarised in Table 3.4 Therefore, they are used in many real-time operations and may obtain good results as shown in simulations. However, such methods require precise information about the environment from accurate sensors to be used in real-time application. Along with this, such methods theoretically do not guarantee an optimal solution neither they are complete in nature (i.e.finding an trajectory in all scenarios). High computational time is another area of concern for such methods in the area of marine robots where on board computational capacity is very

TABLE 3.4: Comparison of APF and Dijkstra in terms of computational time

Approach	Computational Time(s)
Dijkstra	6.80 (**Case 1**)
	5.58 (**Case 2**)
	6.14 (**Case 3**)
APF	32.61

limited.

Compared to such a local approach, heuristic methods are optimal in nature and can intelligently adapt themselves to the ever changing environment. These approaches are complete in nature and provides a faster computation of path in uncertain environment. In the present chapter, a very basic algorithm Dijkstra has shown its computational effectiveness in finding an optimal trajectory in a practical marine environment. In last two decades, significant progress towards the development of heuristic algorithms in robotic path planning has taken place. Very few heuristic studies have been conducted in USV path planning and have been restricted to solutions in static environment. USV path planning in alien dynamic environments with moving obstacles and environmental disturbances is a challenging aspect in an optimal framework. The next chapter will make an effort to implement effective and optimal path planning for an USV in an environment considering moving obstacles and environmental disturbances.

The results of the current chapter has been published as a research article by the International Journal on Marine Navigation and Safety of Sea Transportation which is shown in Appendix B.

Chapter 4

Constrained A* Path Planner

"It is not the ship so much as the skillful sailing that assures the prosperous voyage"

George William Curtis

The current chapter explores an A* approach with an USV enclosed by a circular boundary as a safety distance constraint on generation of optimal waypoints to resolve the problem of motion planning for an USV moving in a maritime environment. Unlike existing work on USV navigation using graph based methods, this study extends the implementation of the proposed A* approach in an environment cluttered with static and moving obstacles and different current intensities. The study also examines the effect of headwind and tailwind currents moving in clockwise and anti clockwise directions respectively of different intensities on optimal waypoints in a partially dynamic environment. The performance of the proposed approach is verified in simulations for different environmental conditions. The effectiveness of the proposed approach is measured using two parameters, namely, path length and computational time as considered in other research works. The results show that the proposed approach is effective for global path planning of USVs.

4.1 Introduction

Recent advances in electronic navigation and intelligent robots have become an imperative aid to navigate marine vehicles effectively for applications ranging from reconnaissance in hostile areas to operations in dangerous weather conditions (Loe, 2008). Path planning is an important layer in the mission management system of an USV voyage. In accordance with the current level of autonomy, USV needs an effective and safe path planning approach in a cluttered operating environment. A substantial amount of research has been conducted in the area of path planning of USVs. Path planning for a USV can be classified into two categories, namely, reactive approaches (Khatib (1986), Borenstein and Koren (1991), Mohanty and Parhi (2013), Fiorini and Shiller

(1998)) where vehicles makes decision *en route* and deliberative approaches where vehicles follows a predetermined path (Hart et al. (1968), Holland (1975), Kennedy and Eberhart (1995)). Several computational approaches comprising of evolutionary methods such as GA or PSO (Zeng et al. (2015), Aghababa (2012)), graph search techniques (Garau et al. (2005), Singh et al. (2017a)), APF (Warren (1990), Singh et al. (2017b)) and FM (Liu and Bucknall (2015), Petres et al. (2007)) have been applied in path planning of marine vehicles.

Ocean environmental effects and moving obstacles play the most significant role in path planning of USV and very few papers have covered their effect on path planning in the last decade (Tam and Bucknall (2010), Statheros et al. (2008)).Neglecting environmental effects in path planning not only leads to significant wastage of energy in USV while navigating in strong currents but could also elevate the potential danger of impact with the obstacles (moving or static) in an ocean environment. In order to save energy, avoid the collision and to increase the endurance of USVs enabled with limited computational resources, it is important to plan the USV voyage in advance before a mission commences by considering environmental effects and dynamic obstacles in the path planning. Traditionally, grid search techniques have been found most efficient in generating a path in the fastest computation time compared to other reactive approaches adopted in path planning of robots (Mohanty and Parhi (2013)).

The chapter is organised as follows : In the current section, the literature pertaining to path planning of USV has been described with major contributions of the current study being explained. In the following section, a detailed overview of the methodology adopted in the current study is presented. In the subsequent section, simulation studies conducted in various environmental scenarios are reported and the proposed approach is benchmarked. The conclusions of the current study are reported in the final section.

4.1.1 Related work

Many studies have been conducted on the subject of grid based path planning in the area of marine vehicles from different perspectives of collision avoidance, heading constraint, environmental disturbances and energy consumption. By reviewing the literature on the subject of optimal path planning in marine vehicles, most of these studies have been in the area of AUV (Alvarez et al. (2004), Garau et al. (2005), Kruger and Briganti (2007), Zeng et al. (2015), Soulignac (2011), Kumar et al. (2005)) and very fewer studies have been in the area of path planning of USV. AUVs cannot operate in all environmental conditions due to limited speed and onboard capabilities against USVs which are more suited for operation in areas of high military, shipping or fishing activity, due to acoustic interference, collision risk, and net entanglement. AUVs are also less well suited to tidally dominated shallow-water settings that have high levels of anthropogenic infrastructure and activity. This leads to a requirement of development for the dedicated path planning approaches for USVs against path planning approaches adopted for AUVs.

The grid based path planning was first proposed in form of the Dijkstra algorithm (Dijkstra (1959)) which was later extended to the A* algorithm by introducing an heuristic cost (Hart et al. (1968)) to speed up the search process by pruning the search space. Generally in grid based path planning, the objective is to find the shortest path by avoiding static obstacles (Stentz (1995)). This approach was first introduced into USV path planning, where an improved three layered architecture towards USV path planning in a harbour was proposed by combining a reactive and A* approach (Casalino et al. (2009)). In another work, a A* approach was extended by combining a grid based path planner with a locally bounded optimal planner towards USV path planning in uncertain sea environment (Svec et al. (2011)). The IMO (IMO (1988), IMO (1995), IMO (2007)) has suggested certain regulations for navigation in a marine environment for collision avoidance commonly known as COLREGs. A COLREGs based A* approach was proposed for way point navigation of an USV complying with Rule 14 of COLREGs in an environment cluttered with static and moving obstacles (Naeem et al. (2006)). A modified A* approach, Finite Angle A*(FAA*) towards obtaining shorter path lengths than classic A* approach has been adopted in a study conducted on USV path planning in an environment comprising static obstacles with a constraint of keeping safe distance from obstacles (Yang et al. (2012)).

Currently a substantial amount of research in mobile robotics towards modifying the conventional A* algorithm to improve its performance as per the mission and kinematic requirement of the robot i.e. A* with Post Smoothing (Rabin (2000)), Field D* (David and Anthony (2005)), Theta* (Nash et al. (2007)) and D* Lite (Koenig and Likhachev (2002)) has been conducted. Owing to technical similarities between mobile robots and USVs, some of the improved approaches have been extended in path planning of USVs. USVs are generally constrained by yaw rate and heading angle in real time manoeuvring. A modified A* algorithm, Theta*, for search in 3D Euclidean space at all orientation was implemented for USV path planning complying with heading angle of USV and compared with conventional grid based 3D path planners (Kim et al. (2012)). In a further work, the Theta* algorithm was improved in terms of computational time and path length against conventional 3D path planners for USV path planning in form of ARC-Theta* algorithm (Kim et al. (2014)), which considers angular rate (yaw rate) of USV in path planning. Another improvement in the A* algorithm for USV path planning was proposed by a modified heuristic for ocean environment with surface currents constrained to heading angle and diverse water depth (Lee et al. (2015)). Another novel work in the area of optimal path planning of USVs has been conducted recently by using FM^2 algorithm, an optimal approach to FM method by considering environmental disturbances (Garrido and Moreno (2016)).

Some novel studies related to use of the FM approach in USV navigation has been investigated recently.Liu and Bucknall (2016b) have proposed a novel method of the modified FM method towards USV navigation in a practical maritime environment. As an extension of the previous study, Liu et al. (2017b) makes an attempt to incorporate a

Kalman filter based prediction method for dynamic obstacles within the modified FM approach.

4.1.2 Problem definition and major contribution

In the present context of autonomy required in the marine environment, autonomous navigation of USVs in a practical marine environment needs to be cognisable of three important issues, namely, safety, reliability of the mission and likelihood of the success (Statheros et al. (2008), LaValle (2006)). Central to the path planning algorithms, two approaches are widely adopted namely, a waypoint approach and a trajectory based approach. The way point approach is associated with non parameterized straight line paths generated from connection of waypoints while trajectory based approach is associated with time parameterized path to convert the waypoint paths into dynamic trajectories (Şerban (2016)). The present study adopts a way-point approach over trajectory based approach for a USV named, *Springer*, shown in Figure 3.4, navigating in a practical marine environment due to its easier implementation in practical scenarios (Fossen (1995)). The specifications of *Springer*, available at the University of Plymouth, are tabulated in Table 3.1. USVs operate in an environment where ocean environmental effects and moving ships have a significant effect on the way-point selection for an USV voyage based on mission requirement. These mission requirements can be classified in small-scale and large-scale operations. Small-scale operations include bathymetric surveys, pollution monitoring and data assimilation in a cluttered environment where the generation of safer way-points have the highest priority in the path planning while large-scale operations include trans-oceanic voyage and cooperative surveying where the shortest distance is required for high endurance. Hence there is a challenge to conserve energy as well as consider safety of USVs in USV path planning for USVs designed with heterogeneous mission requirements in mind.

Ocean environmental effects can be bifurcated into three streams, as the additive and multiplicative disturbances on vehicle hull, namely, wind, waves and ocean currents (Fossen (1995)). Wind load is generally ignored in path planning since USVs have a high draft compared to an air projection area and operations are generally restricted in an environment with wind speed less than 10 m/s (Lee et al. (2015)). In order to simulate the motion of USVs, it is generally assumed that wave loads account for fluctuating pressure distribution below the water surface and the water surface remains unaffected (Fossen (1995)). Hence wave loads become more significant in dynamic positioning than path planning. Wind generated currents have the highest significance on path planning and way-point generation. Since the Earth is rotating, the Coriolis force turns major currents to the right in the northern hemisphere while opposite in southern hemisphere (Fossen (1995)) as viewed from above. Consequently, another major challenge is to understand the steady non uniform headwind and tailwind (Knight (2008),Belcher (2007)) currents effect on way-point generation and optimality in grid-based path planners. This challenge becomes more complex when uncertain obstacles in the form of moving obstacles appear in the operational domain of an USV.

The work of Kim et al. (2014) has showed that conventional A* outperforms other heuristic variants of A* in terms of computational time and Euclidean distance in a maritime environment. Henceforth, leading to requirement of developing a computationally effective version of A* by adopting the conventional A* approach. In order to address aforementioned challenges and issues pertaining to the autonomy of USVs, the current study adopts an A* approach with an USV enclosed by a circular boundary as a safety distance constraint on generation of optimal waypoints. This resolves the problem of optimal path planning for an USV moving in a practical maritime environment, leading to generation of safer way-points with conservation of energy. Figure 4.1 describes a comparison of the path generated by conventional grid-based method against the path generated by conventional grid-based method considering safety distance and surface ocean currents. To the best of the authors knowledge, such an approach has not been adopted and studied towards USV path planning in a cluttered environment having static and moving obstacles in addition to surface currents. USVs are mostly equipped with limited computational resources in addition to limited endurance. This chapter assess the effectiveness of the proposed approach in terms of computational time to generate path and path length in simulation studies conducted in various environmental scenarios.

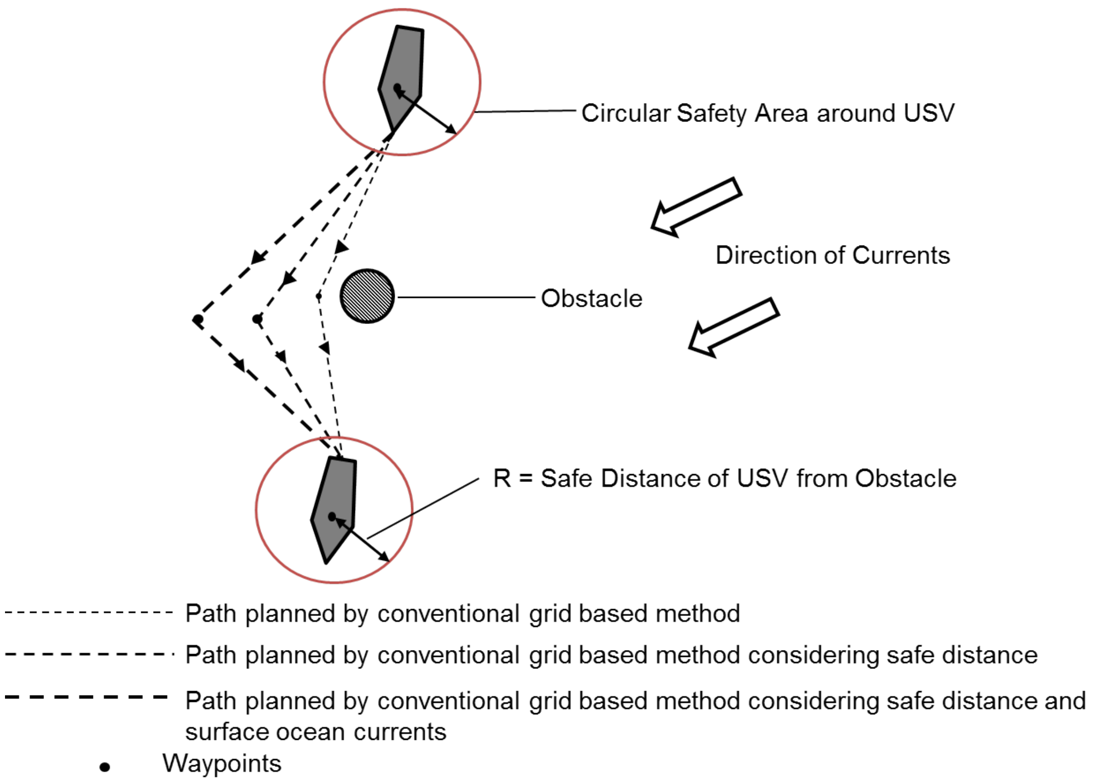


Figure 4.1: A schematic showing the path generated by a conventional grid based path planner compared against the path generated by a grid based path planner by considering safety distance and sea surface currents (clockwise). In case of anti clockwise currents, the sea surface currents push the USV towards the obstacle and the proposed algorithm makes sure that a safety distance is maintained to ensure no collision

4.2 Methodology Overview

4.2.1 Environmental mapping

The abstraction of path planning for USVs is shown in Figure 4.2. In order to implement path planning algorithms, mapping the environment becomes the initial step. Environmental mapping converts world space into Configuration space (Cspace) which helps in quick implementation of algorithms and manageable storage in computers (Mooney (2009)). The Cspace for the USVs are dynamic in nature with high spatial and temporal variability. This chapter adopts a popular mapping technique, namely, regular occupancy grid due to its effective resolution in grid based path planners (Mooney (2009)). Portsmouth harbour is among the busiest harbours in United Kingdom and is a perfect area for understanding path planning of USVs. In this study, binary images of satellite images of Portsmouth harbour taken from *Google Maps* have been utilised as gridded maps for the proposed A* approach as shown in Figure 3.3. The Cspace for the planar USV is considered as R^2 , representing the planar positions of the USV where an USV is treated as a pixel point on the map. The map of the environment is the converted binary image where free space is considered as 1 (white) while obstacle is considered as 0 (black). The 800×800 binary image has a resolution of 3.6 m per pixel length.

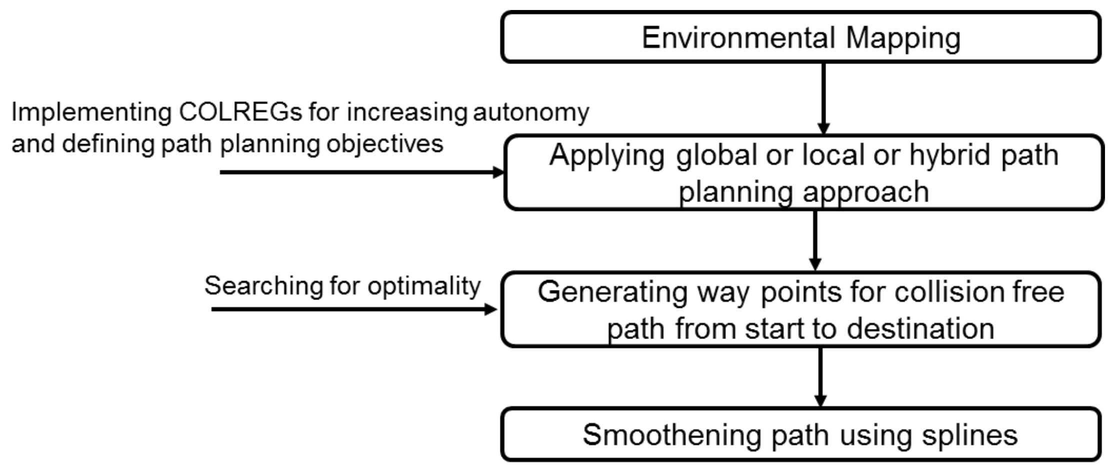


FIGURE 4.2: Path planning abstraction for USVs

4.2.2 A* Algorithm

The choice of approach is the next step in path planning of USVs. In the present study, the A* approach with safety distance constraints has been adopted. Adoption of certain path planning approaches in an USV is mission dependent. Since the current study considers an USV, *Springer*, developed with primary purpose of monitoring sea pollution, generation of safer way points with conservation of optimality for higher endurance becomes the highest priority. Although several approaches have been adopted in the literature (Section 4.1.1), no approach has been able to compute path with a better computational time than the conventional A* approach in simulation studies.

The A* algorithm on a gridded map is restricted either to 4-connectivity or 8-connectivity, as shown in Figure4.3, based on resolution required, where each cell in Cspace is evaluated by the value:

$$f(n) = h(n) + g(n) \tag{4.1}$$

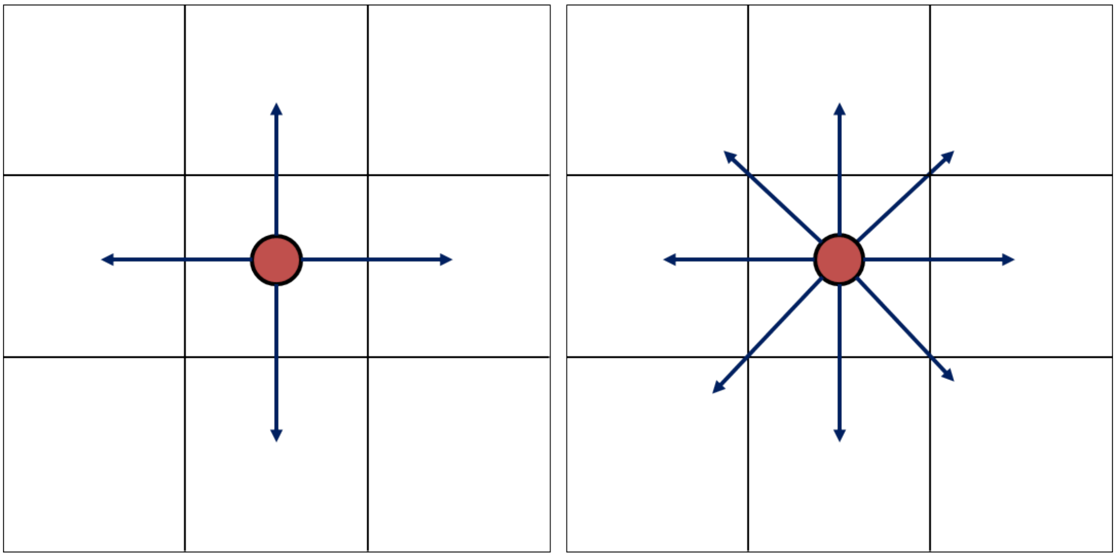


FIGURE 4.3: Schematic of 4-connectivity and 8-connectivity in Cspace

where, $h(n)$ is the heuristic distance of the cell to the goal state and $g(n)$ is the length of the path from initial state to goal state through selected sequence of cells. Each adjacent cell of actually reached cell is evaluated by value of $f(n)$ and the one with lowest value of $f(n)$ is chosen as the next one in sequence. This advantage of modifying distance in A* gives a wide range of modifications which can be applied in the algorithm in the form of energy consumption and safety distance (Duchoň et al. (2014)). The present study considers the safety distance constraint to study the path planning of USVs. The pseudo code for A* algorithm is defined in Algorithm 1.

In Algorithm 1, A* use a priority queue to perform the repeated selection of minimum (estimated) cost nodes to expand. This priority queue is known as the *openset* or *fringe*. At each step of the algorithm, the node with the lowest f value is removed from the queue, the f and h values of its neighbours are updated accordingly, and these neighbours are added to the queue. The algorithm continues until a goal node has a lower f value than any node in the queue (or until the queue is empty). The f value of the goal is then the cost of the shortest path, since h at the goal is zero in an admissible heuristic.

Algorithm 1: A* Algorithm

```
Data: start, goal(n), h(n), expand(n)
Result: path
Begin;
if goal(start) = true then
    return makePath(start)
end
open ← start
closed ← ∅
while open ≠ ∅ do
    sort(open) ;
    n ← open.pop() ;
    kids ← expand(n) ;
    forall kid ∈ kids do
        kid.f ← (n.g + 1) + h(kid);
        if goal(kid) = true then
            return makePath(kid);
            if kid ∩ closed then
                open ← kid;
            end
        end
    end
    closed ← n
end
return ∅
```

4.2.3 Comparing A* approach with safety distance for different resolution

Fig. 4.4 shows the comparison of the A* approach for 4-connectivity and 8-connectivity on a gridded map in terms of computational time. The results show that on a R^2 grid map, 4-connectivity resolution produces a computationally efficient path in a A* approach against path produced by 8-connectivity resolution. This is owing to the fact that search process explores lesser number of nodes by pruning the search domain.

Although, in terms of path length, simulations shows that the A* approach with 8-connectivity resolution produces a better path than 4-connectivity resolution with a more better quality of path as shown in Fig. 4.6. This difference in resultant paths due to the fact that search process explores more number of nodes in an 8-connectivity resolution on a R^2 grid map.

Since 8-connectivity resolution produces a more optimal path as shown from the values shown in Fig. 4.5 with more better resolution as explained above. Hence, the current study adopts a 8-connectivity resolution for effective global path planning of USV in a constrained channel of Portsmouth harbour.

The proposed study deals with inclusion of a safety distance criteria in the A* approach towards USV path planning. In order to benchmark, a safety distance of 10

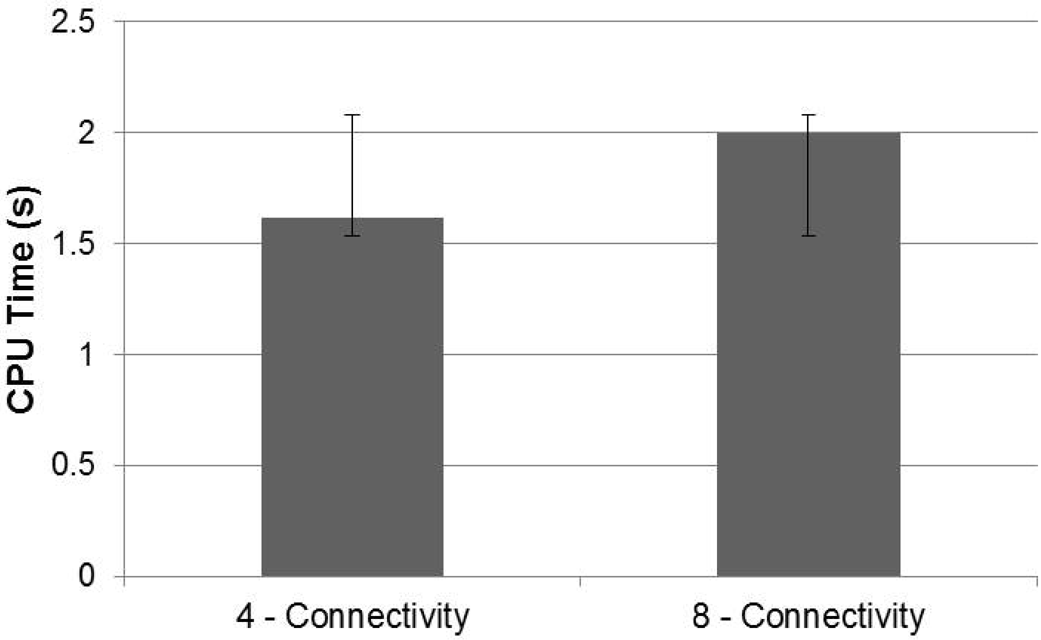


FIGURE 4.4: Compared computational time of the A* approach with 4-connectivity and 8-connectivity resolution. The interval on each bar denotes the standard deviation of the computational time

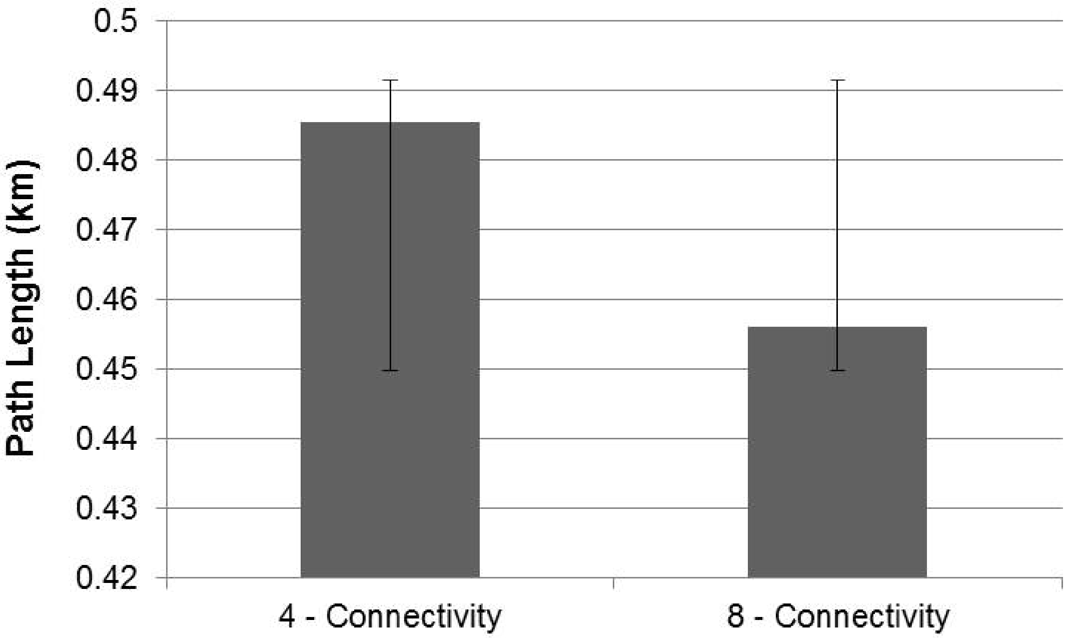


FIGURE 4.5: Compared path length of the A* approach with 4-connectivity and 8-connectivity resolution. The interval on each bar denotes the standard deviation of the path length

pixels is arbitrarily chosen on a grid map. Two cases of 4-connectivity and 8-connectivity on a gridded map is compared in terms of the quality of the path obtained and path length.

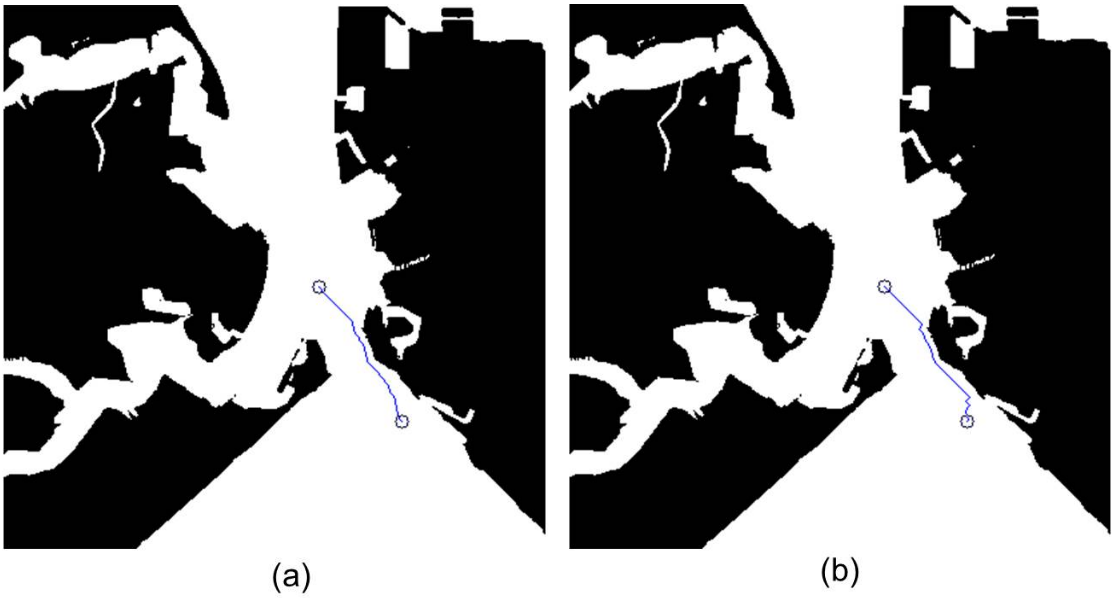


FIGURE 4.6: Resultant paths with (a) 8-connectivity (b) 4-connectivity resolution

4.2.4 Assumptions

The complexity of USV path planning is massive and a number of simplifications have been recommended to reduce the intricacies of the problem (Azariadis and Aspragathos, 2005). Here, the following assumptions have been made:

1. The map (study area) is considered to be in a confined sea environment near to Portsmouth harbour. Henceforth, temporal and spatial variability in the chosen study area in terms of environmental effects and moving vessels is considered quasi-static for the period of the USV voyage.

2. Kalman filter and other sensor measurements are used on a USV to determine the obstacle position over time. The current study assumes that position and velocity of the moving obstacle in Cspace is known from a Kalman filter.

3. The given moving obstacles are modelled as ellipses on the grid map by combining two grid points, where each grid point comprises of a semi ellipse, since it is a standard practice in a marine environment to consider moving obstacles in an elliptical domain as per the recommendations of the IMO (Tam et al. (2009)). Overlapping of elliptical shape with grid cell boundary is neglected.

4. The USV is modelled as a particle under the assumption that an effective, robust controller quickly establishes the commanded velocity.

5. The USVs are generally having a combination of deliberative and reactive systems on board for planning path in a marine environment. The deliberative systems help in determining global waypoints, while reactive systems are responsible for collision avoidance when dynamic obstacles come in the USV safety domain described in

Figure 4.1. It is assumed that such reactive collision avoidance takes over in off-nominal conditions, such as a case where a previously undetected obstacle appears or global path planner fails to generate a path.

A schematic of the path planning system adopted in the current study is shown in Figure 4.7. Information of sea surface current, moving obstacles and topography of the study area is used to define the map in the form of a graph and the proposed approach is used to generate safer waypoints for an optimal path.

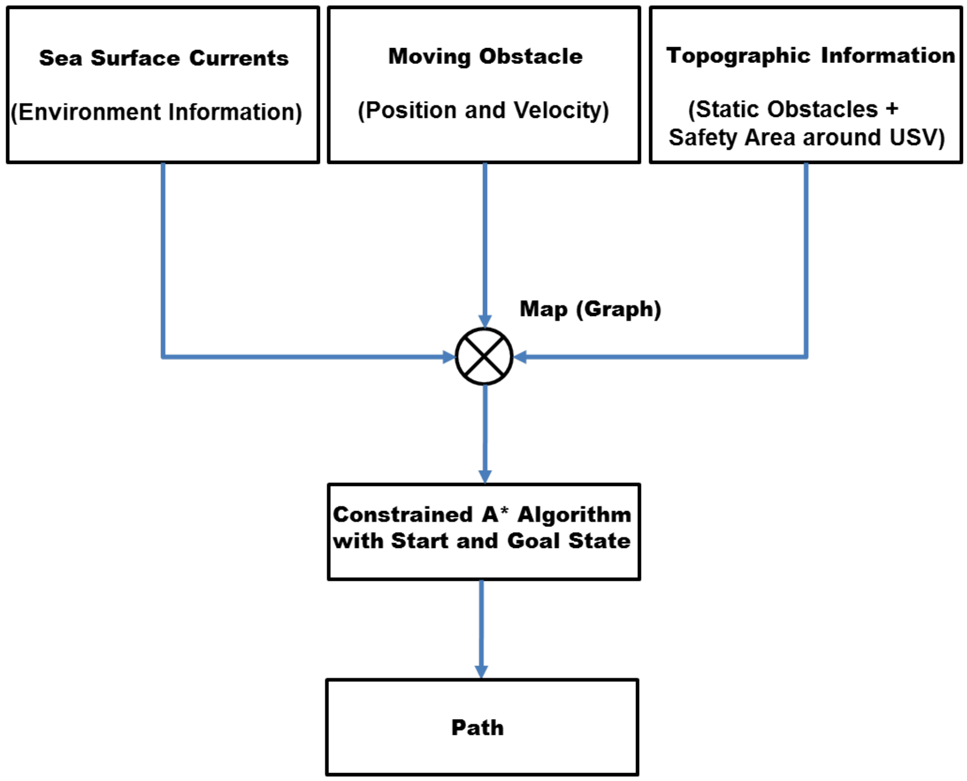


FIGURE 4.7: Schematic of the proposed path planning system

4.2.5 Incorporating Guidance and Control System with Path Planning Algorithm

The general architecture of an USV operation in a maritime environment has basically three subsystems, namely, control and path planning, ODA and communication and monitoring as shown in Figure 2.4.Path planning is an important subsystem of this architecture responsible for generating waypoints within a desired environment. The current study proposes a computationally effective and safer approach for generation of optimal waypoints for USV navigation in the desired environment. In order to plan and execute a mission in real-time, it is hereby important to interface the guidance and control subsystems with navigation methods and provide quick feedback to the guidance and control subsystems for effective decision making and higher autonomy.

Conventional waypoint guidance subsystems are designed by reducing surge, sway and yaw (3 DOF) to surge and heading (2 DOF) (Healey et al. (1992)). Guidance is responsible to achieve motion control objectives in the physical environment in which the vehicle moves (Bibuli et al. (2009)). The easiest way is to use a classical autopilot system, so that commanded yaw angle generated from a line-of-sight (LOS) guidance algorithm can be controlled (assuming sufficient bandwidth) and cross track error is minimised. Figure 4.8 shows a waypoint tracking control system implemented with a standard PID autopilot in series with a LOS algorithm. In this figure, the way points generated from the offline path planners are given as an input to the LOS algorithm which calculates the reference heading angles to be followed by the controller. The PID control approach is then used to follow this reference trajectory by minimising the cross track and along track errors.

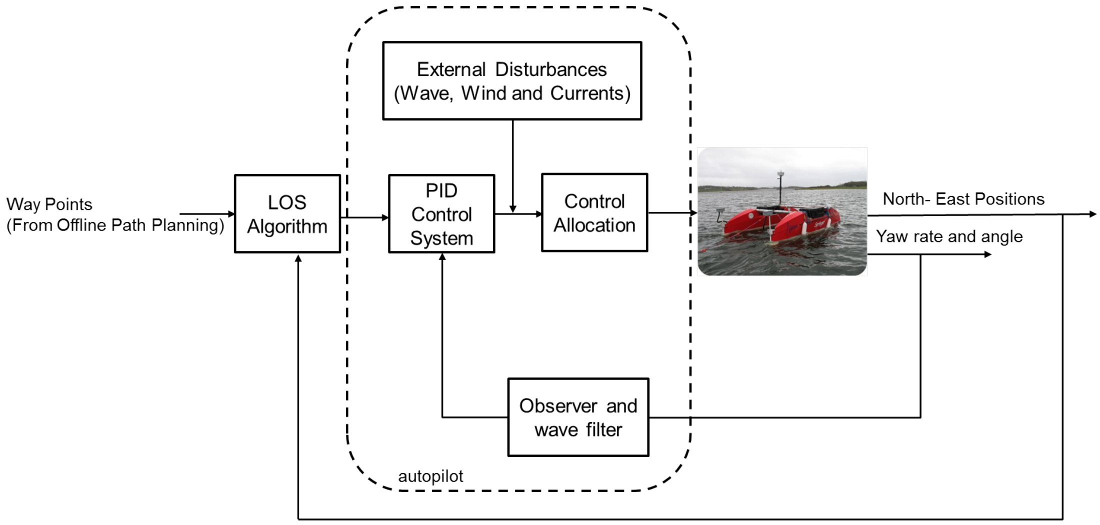


Figure 4.8: PID autopilot with a LOS projection algorithm for way-point tracking (Source: Modified from Fossen et al. (2003))

The waypoints expressed in the current study are in terms of pixels which need to be converted to absolute location on earth by combining the latitude, longitude and elevation of the earth for real world navigation. The work of Massey (2006) shows that if the vehicle approaches waypoint with slight offset, it causes huge heading error ranging from 1-2 degrees to 80+ degrees primarily due to GPS heading, coordinate transformation and well as steady state error in the controller. A simple and robust approach to correct this problem involves defining a circle of specified radius around waypoint or the USV. The current study has adopted the approach of having a circle around USV with the USV being treated as a particle to solve this heading and path error. As soon as waypoint comes within that circle of USV, it is assumed that waypoint is safely achieved.

In terms of autopilot and control system development, a detailed review of studies conducted on USVs has been discussed by Roberts (2008). Many control techniques like H_∞ (Lefeber et al. (2003)), linear quadratic Gaussian (LQG) (Sharma et al. (2012)), model predictive control (MPC) (Annamalai et al. (2015)) have been proposed recently, together with development of an adaptive control system (Sharma et al. (2014)) towards making the controller effective for a range of USV speeds and operating sea conditions.

4.2.6 Collision avoidance in close encounter situation

The general architecture for a USV operation in a maritime environment described in Figure 2.4 shows that high level planners send waypoints to low level decision makers i.e. local control systems and obstacle avoidance subsystems to execute the waypoint following task. When a time variant moving obstacle enters the working domain of the operating USV, it is expected that high level planners quickly regenerates new set of way points based on the current information of the environment. Many other factors like relative velocity of the USV and the obstacle , the sensing horizon etc also plays an important role in such regeneration process. In such transition, it is hereby required to have a quick response time from the high level planners, which is one of the main objectives of the current study.

In real-time operations, collision avoidance is the most important objective. Since the current study considers inland UK water for operation of USVs, it is imperative to follow the local guidelines towards the development of a path planner and collision avoidance with moving obstacles. To enable the safe and secure operation of autonomous surface ships within the existing IMO requirement, a code of practice has been prepared by the UK Maritime Autonomous Systems Working Group (MASRWG) and published by Maritime UK through the Society of Maritime Industries (UK (2017)). Under this code of practice, all autonomous ships working within UK waters have 6 levels of autonomy as developed by the European Defence Agency as follows (UK (2017)):

1. Human on Board
2. Operated
3. Directed
4. Delegated
5. Monitored
6. Autonomous

The current state of operation of USVs is either at level 3 or level 4 of the autonomy, where there is always a human-in- the loop towards monitoring the operation of USVs. It should be noted that the autonomy levels from 2 to 5 as mentioned have humans involved in the process of operation of USVs. Human monitoring ensures that in the case of any failure of the on-board system, they can override the system and can ensure the safety of the operation of the USVs. In a case where an unknown obstacle of uncertain trajectory and nature enters into the domain of the USV and collision cannot be avoided, a few emergency actions like abort and stop are employed in response to fault conditions.

4.3 Simulation Results

The proposed approach is simulated using C++ and OpenCV. All simulations are performed on a PC with *Microsoft* Windows 7 as OS with Intel i5 2.70 GHz quad core CPU and 16 GB RAM. In real time simulation, the processes are executed with a fixed time step to solve the functions involved with the process. The CPU of the computer sometimes overestimate and underestimate the time involved in the computation of these functions. Hence it is a standard practice to take the average of the overestimated and underestimated time of the computation by taking the average time of the multiple computations. The simulations were repeated for 500 times, especially in terms of computational time, to account for variable computational power in OS Windows. The average time from all repetitions was calculated for proper verification of the proposed approach.

4.3.1 Comparing A* approach with and without safety distance

The proposed study deals with inclusion of a safety distance criteria in the A* approach towards USV path planning. In order to benchmark the safety distance approach and to decide upon an optimum value of safety distance, four arbitrary values, 10, 20, 30 and 40 pixels are taken as safety distance on a grid map (as shown in Figure 4.1) and compared against an A* approach without safety distance in terms of computational time. The start and goal states used in the path planning system are depicted on the binary map as shown in Figure 4.9.

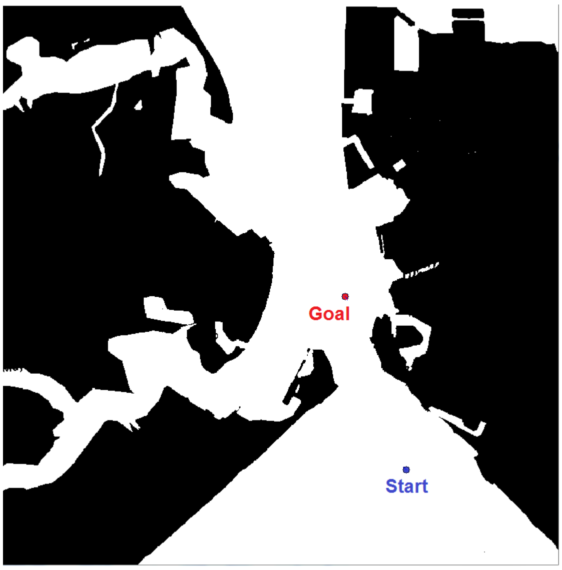


FIGURE 4.9: Binary map with start and goal states

Figure 4.10 shows the comparison of A* approach with and without safety distance constraint in terms of computational time. The results show that on a R^2 grid map, a larger safety distance constraint produces computationally efficient path in a A* approach against paths produced without such constraint. This is due to the fact that search process explores lesser number of nodes with safety distance than without safety distance by pruning the search domain. The increased safety distance makes a decrease in the computational time to compute the path. It must be noted from Figure 4.11 that increased safety distance also changes the list of the waypoints which the vehicles need to follow as it goes from start to goal point.

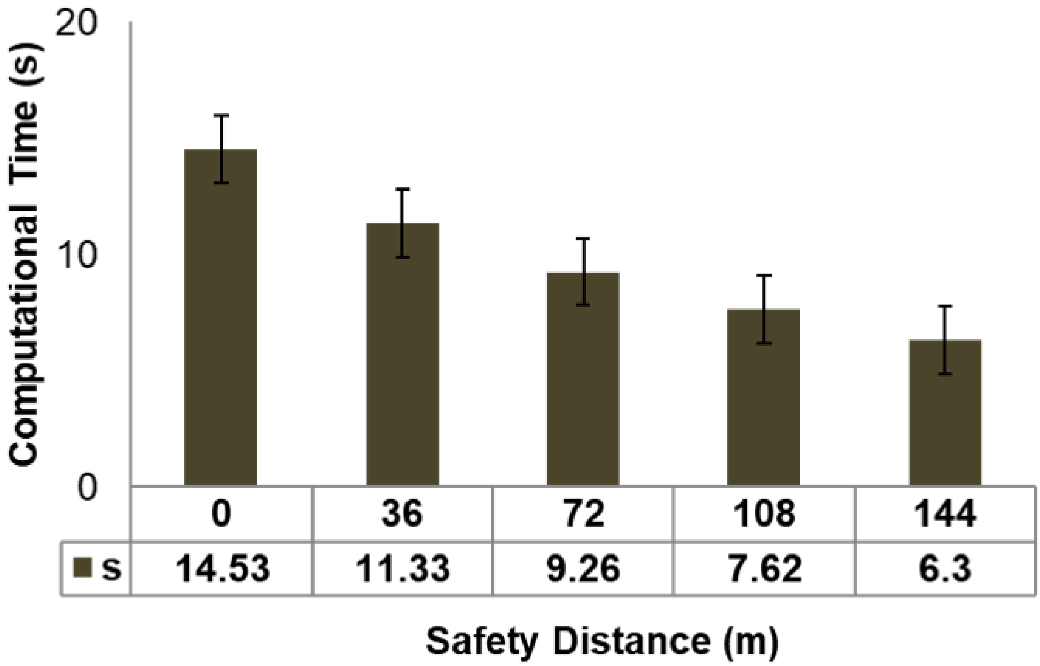


FIGURE 4.10: Compared computational time of A* approach with and without safety distance constraint. The interval on each bar denotes the standard deviation of the computational time

In terms of path length, simulations shows that the A* approach with and without safety distance constraint produces path of equal length i.e. 1.043 km although a difference in resultant path can be seen in Figure 4.11. This difference in resultant paths is less visible in smaller safety distance values while a more noticeable difference is observed in paths produced with larger safety distance. This leads to the fact that optimality remains conserved in path planning with decrease in computational effort in the proposed approach unlike ones adopted in literature towards path planning of USVs where an increase in computational cost has been observed with increase in path length for proposed approaches.

Since the current study considers a narrow channel of Portsmouth harbour for path planning of USV, henceforth, it becomes necessary to choose a safety distance where a proper trade off between computational time and safety distance from an obstacle can be maintained. Therefore, a 20 pixel safety distance (72 m on real map) has been chosen for the present study. This value also provides enough time for local reactive techniques for collision avoidance in case where one or more moving obstacles are detected in the operational domain of the USV.

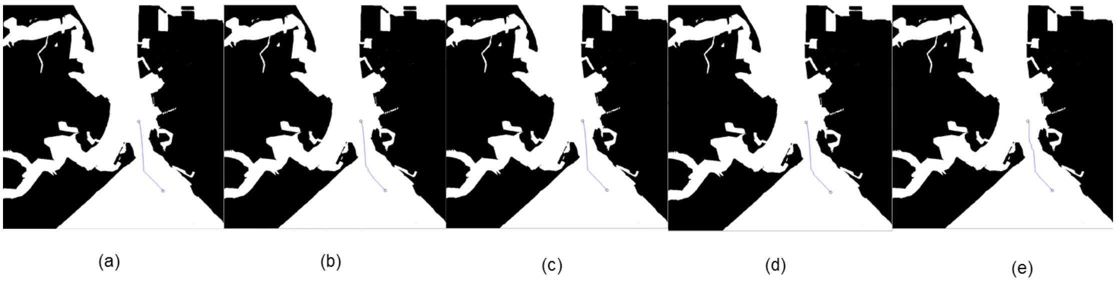


FIGURE 4.11: Resultant path with safety distance of (a) 0 (b) 10 (c) 20 (d) 30 (e) 40 pixels

4.3.2 Constrained A* approach under static and partially dynamic environment

In order to understand the effectiveness of the proposed approach, simulations are conducted in binary maps of Portsmouth harbour comprising of static obstacles as well as moving obstacles. Such an environment which consists of moving and stationary obstacles is termed as a partially dynamic environment. The effectiveness is defined in terms of path length and computational time obtained in simulations. In simulations, a stationary map with one and two moving obstacles for a constrained channel having start and goal points as defined in Figure 4.12 in Portsmouth harbour has been considered. A binary map of the simulation area with single and two moving obstacles is shown in Figure 4.13.

FIGURE 4.12: Binary map with start and goal states for simulating A* approach under static and partially dynamic environment

FIGURE 4.13: Binary map of the simulation area (Portsmouth harbour) showing velocity and direction of moving obstacles. In this study, 20 pixels has been chosen as the safety distance around an USV.

Modelling of dynamic obstacles on a map for maritime path planning is defined in terms of the velocity of the moving obstacle in maritime environment. Liu and Bucknall (2015) has suggested a circular shape for slow moving obstacles and elliptical shapes for fast moving obstacles. Therefore, an elliptical shape as shown in Figure 4.14 has been adopted in the current study.

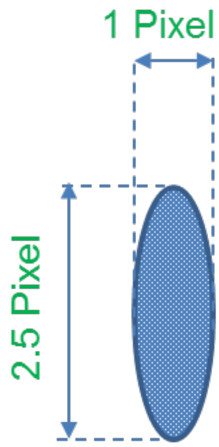


FIGURE 4.14: Dimension of the elliptical domain representing the encapsulation of a moving obstacle in a static one in the binary map. The dimensions of ellipse are chosen in accordance with the dimensions of high speed craft having operational velocity range from 6 to 9 knots

The results presented in Figure 4.15 shows path generated by the proposed approach in different scenarios of single moving obstacle. The scenarios presented in the figure show a single moving obstacle moving in a straight line at a velocity of 6 knots, based upon its start point shown in Figure 4.12 and considers each instantaneous dynamic situation as static (based on the conventional method adopted in deliberative path planning by Borenstein and Koren (1991)). Path length and computational time are computed for each start time of the mission and results are shown in Figure 4.16 and Figure 4.17. It is found that as the moving obstacle approaches the safety domain of the USV, an increase in path distance is observed.

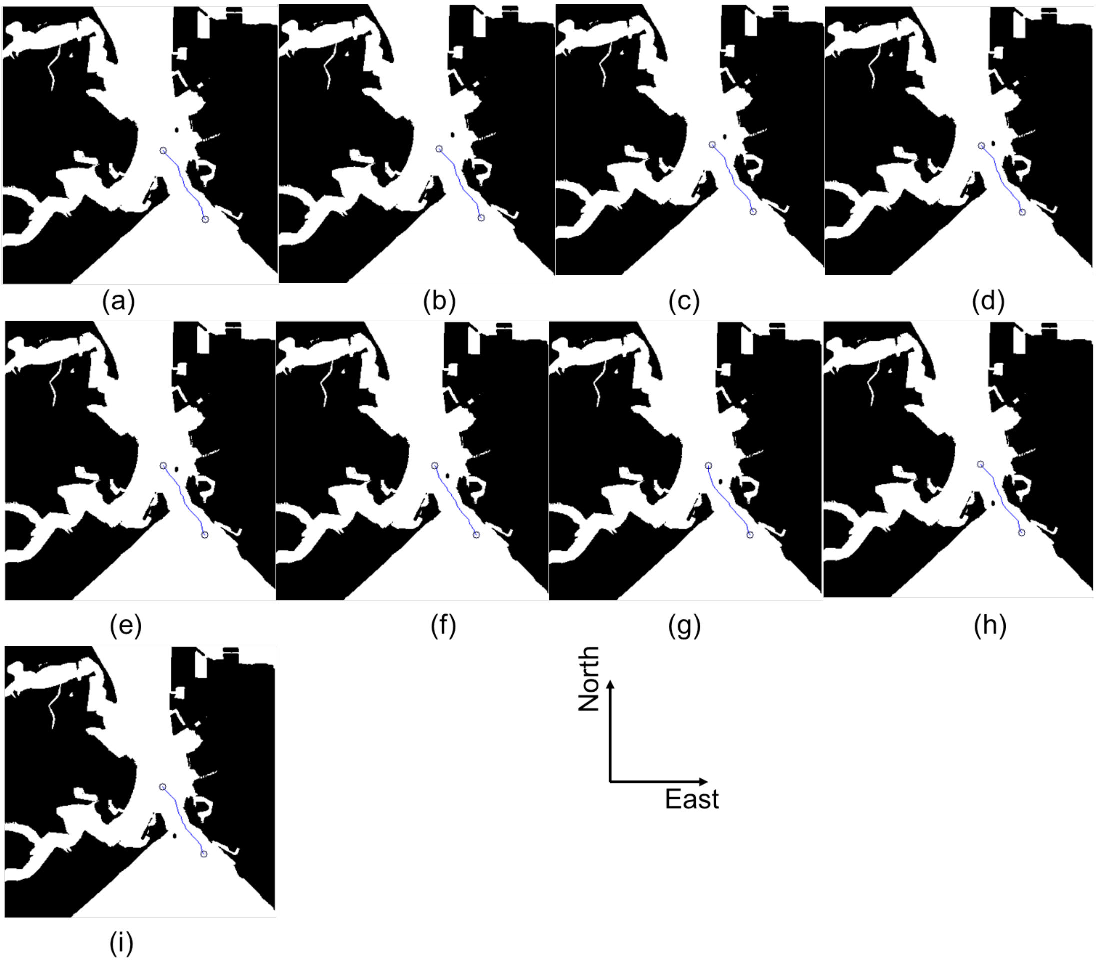


FIGURE 4.15: Comparison of paths obtained with different start time (a) 0 (b) 10 (c) 20 (d) 30 (e) 40 (f) 50 (g) 60 (h) 100 (i) 120 seconds. Position of the single moving obstacle is plotted at each start time on the binary map, based on the velocity and direction mentioned in Figure 4.13

This is owing to the fact that vehicle moves further east, as shown in Figure 4.15(h), to maintain the constraint of keeping a safety distance of 20 pixels. In addition to that a decrease in computational effort is observed with increase in path length once the moving obstacle is detected within the safety domain of USV. This is because the search space in the gridded map gets pruned in the proposed approach which leads to generation of longer path length with decrease in computational time. The computational time again increases once the moving obstacle escapes out of the safety domain of the USV.

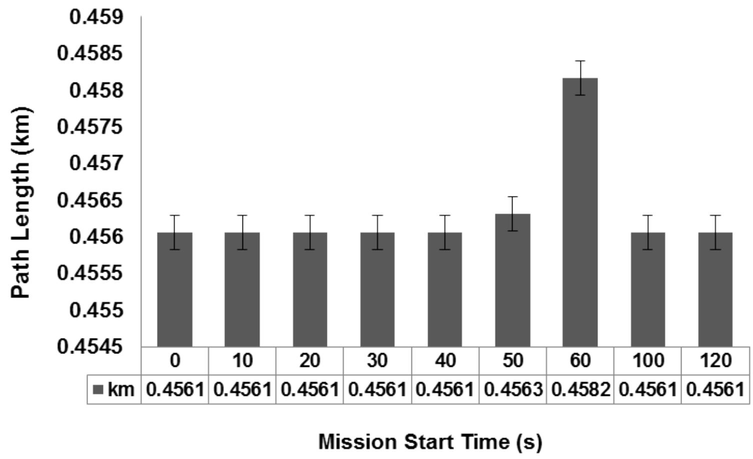


FIGURE 4.16: Comparison of path length obtained with different start time (a) 0 (b) 10 (c) 20 (d) 30 (e) 40 (f) 50 (g) 60 (h) 100 (i) 120 seconds. A safety distance constraint of 20 pixel is maintained for all scenarios in the figure. The interval on each bar denotes the standard deviation of the path length.Km represents Kilometer

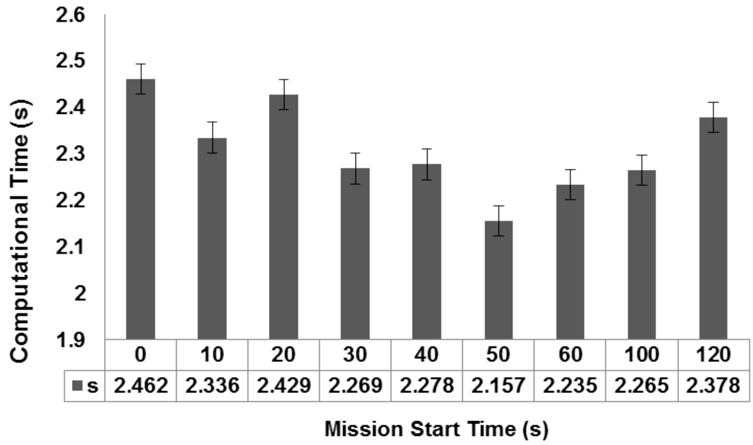


FIGURE 4.17: Comparison of computational time obtained with different start time (a) 0 (b) 10 (c) 20 (d) 30 (e) 40 (f) 50 (g) 60 (h) 100 (i) 120 seconds. The interval on each bar denotes the standard deviation of the computational time

From the Fig 4.16 and Fig 4.17 it is evident that the most optimum computational time to determine path is for a 50s mission start time. It is owing to the fact that the most least number of nodes are being explored by the algorithm in this case to determine the path. It must be noted that the path length obtained for 30s and 40s are same although there is a difference in the computational time to determine the path. The 40s takes more time than 30s. It is due to the number of nodes being explored in each case. In order to make the environment more complex and more cluttered, a scenario with two moving obstacles is considered for understanding the effectiveness of the proposed approach as shown in Figure 4.13(right side). The results shown in Figure 4.18 shows path generated by proposed approach in different scenarios of an maritime environment with two moving obstacles. The scenarios presented in the figure shows both moving obstacles are moving in a straight line at a velocity of 6 knots, based upon their start points shown in Figure 4.12.

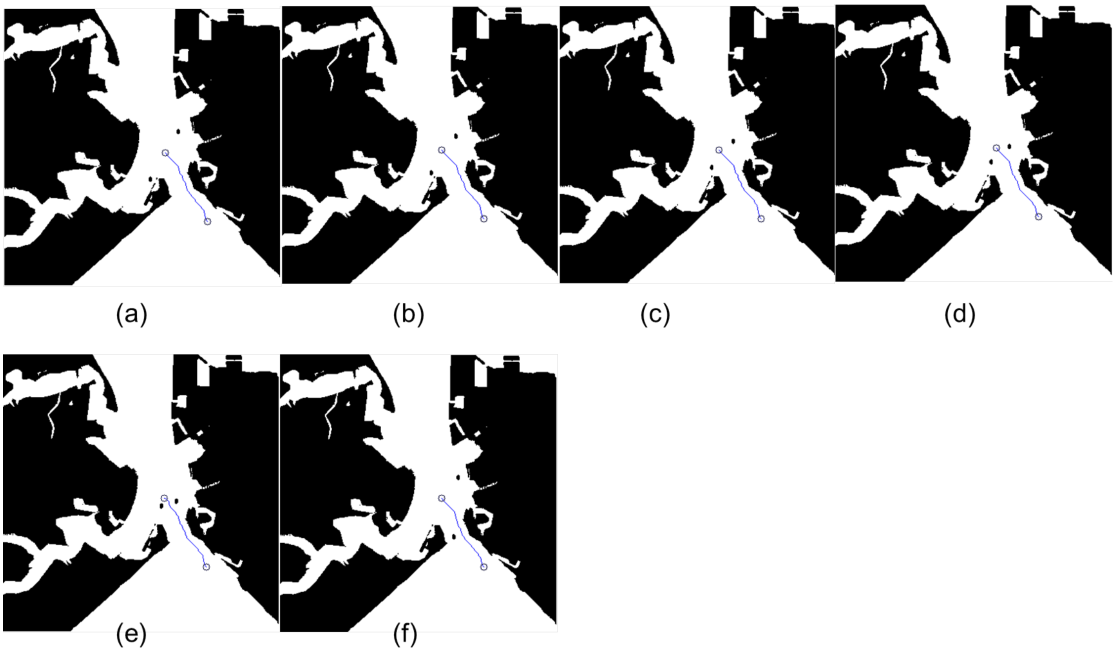


Figure 4.18: Comparison of paths obtained with different start time (a) 0 (b) 10 (c) 20 (d) 30 (e) 40 (f) 100 seconds. A safety distance constraint of 20 pixel is maintained for all scenarios in the figure.Position of both moving obstacles is plotted at each start time on the binary map, based on the velocity and direction mentioned in Figure 4.13.

In this case also the same pattern as found with the single moving obstacle scenario is observed. The comparison of path length and computational time is shown in Figure 4.19 and Figure 4.20 respectively. The path length increases once the moving obstacles approaches the safety domain of the USV in order to maintain the safety distance constraint. This fact is reflected in the resultant paths obtained in different scenarios where a change in resultant path is obtained when moving obstacle approaches USV. With increase in path length, a decrease in computational time is observed. The computational time retains the increased value once the moving obstacles escape out of the safety domain of the USV.

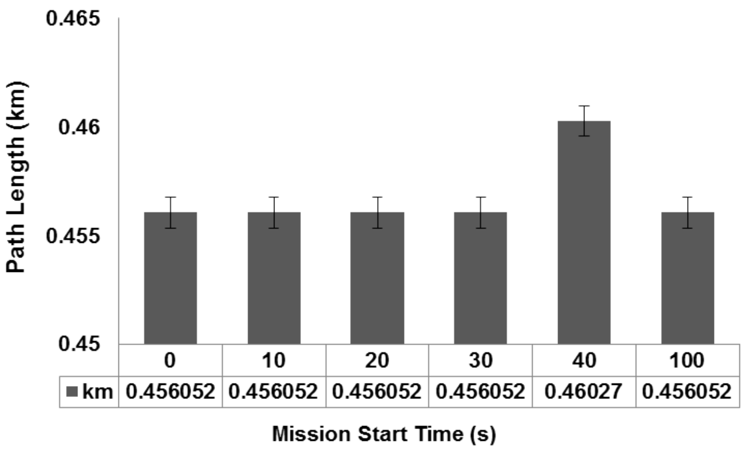


Figure 4.19: Comparison of path length obtained with different start time 0, 10, 20, 30, 40 and 100 seconds.The interval on each bar denotes the standard deviation of the path length. Km represents Kilometer

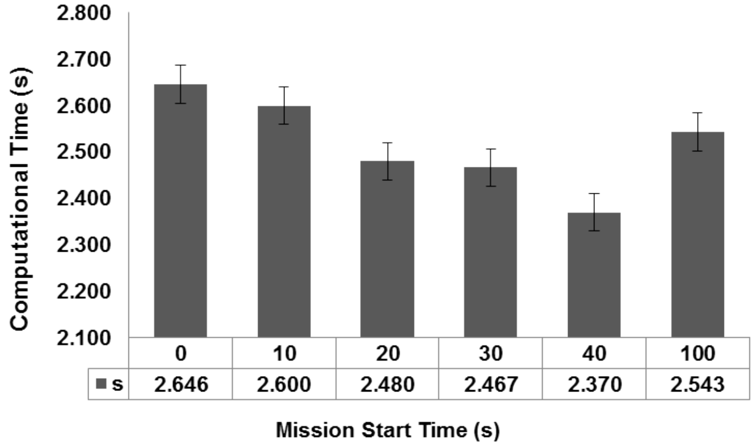


FIGURE 4.20: Comparison of computational time obtained with different start time of 0, 10, 20, 30, 40 and 100 seconds. The interval on each bar denotes the standard deviation of the computational time

4.3.3 Constrained A* approach with environmental disturbances

Ocean currents generated in the upper layer of the ocean environment by atmospheric wind system are referred as sea surface currents (Fossen (1995)). In the current study, the effect of steady non uniform headwind and tailwind currents on USV navigation has been studied for the proposed approach. In general, ocean currents are provided in a NetCDF data format by various meteorological agencies around the world. Such data obtained from satellites have a resolution of 2 km (Bonnett and Campbell (2002)) while the range of most navigation devices is less than 5 nmi which makes such data low in precision and not suitable for USV path planning. Hence, the synthetic vector field of moderate and strong intensity is created within the map to verify the effect of current on optimal path planning. Real ocean currents are multi-directional and irregular, spatially and temporally. In the present study, current effect on USV path planning is simplified as a constant disturbance by assuming the current to be unchanged over a period of time (Antonelli et al. (2008)). Two current scenarios, a moderate current intensity of 1.5 m/s and a strong current intensity of 2.5 m/s is considered for the present study. These values are chosen on observation of high speed currents of 2 to 3 m/s in coastal regions (Fossen (1995)).

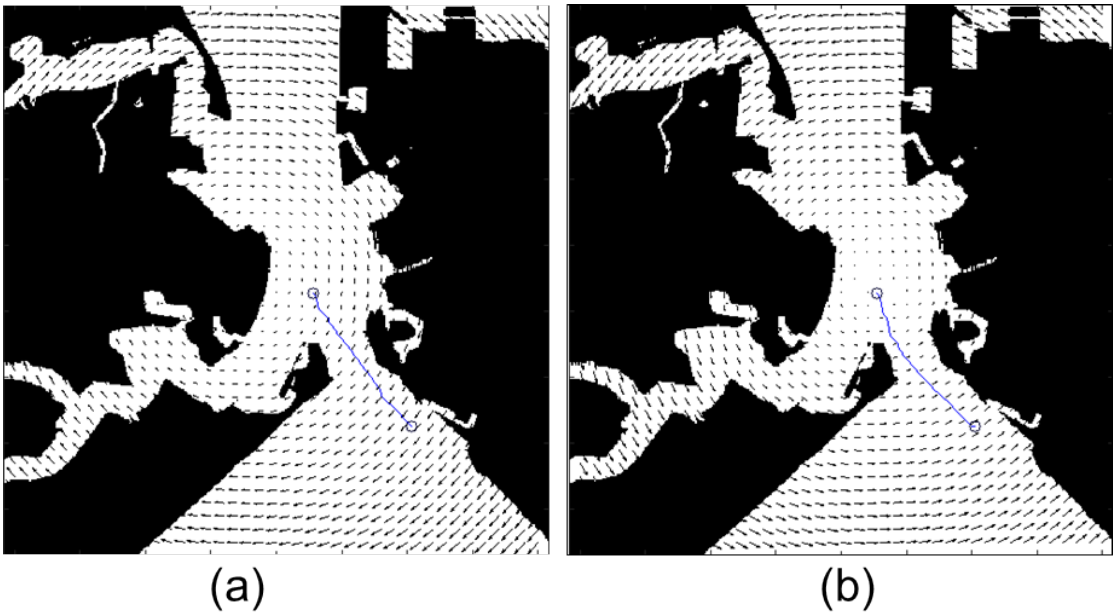


FIGURE 4.21: Comparison of paths obtained for currents moving with intensity of 1.4 m/s in (a) anti-clockwise and (b) clockwise direction. The start and goal states are same as shown in Figure4.12. The safety distance constraint of 20 pixels is maintained for both scenarios.

In order to understand the steady non uniform headwind and tailwind effects of current on path planning, clockwise and anti-clockwise directions of chosen intensity values are taken in the present study. Figure 4.21 shows the path obtained by the proposed approach with currents moving in anti-clockwise and clockwise direction with intensity of 1.4 m/s. Path length and computational time are compared for both scenarios shown in Figure 4.1 and results are presented in Figure 4.22 and Figure 4.23 respectively. The results shows that when the USV operates in steady non uniform tailwind currents, it has to cover a larger distance in current while a smaller distance is observed in steady non uniform headwind currents. This is due to the fact that presence of steady non uniform tailwind currents in the USV voyage creates larger forces in the sway motion, directing the USV to move closer to the shore line (as seen in Figure 4.21(a)), which leads to generation of a path with a longer curvature. The current approach has been able to demonstrate a decrease in computational effort to find path when higher distance voyages are observed under influence of sea surface currents.

Along the same line, currents of 2.5 m/s are considered to understand the path planning pattern of USV under influence of strong ocean currents. Figure 4.25 shows the path obtained by the proposed approach with currents moving in anti-clockwise and clockwise direction with intensity of 2.5 m/s. Path length and computational time are compared for both scenarios shown in Figure 4.25 and results are shown in Figure 4.23 and Figure 4.26 respectively. In this case also, a similar pattern as found with 1.4 m/s has been observed. In terms of current intensities of different magnitude moving in same direction (from a comparison of path length values for AC currents in Figure4.22 and Figure 4.25), it has been found that currents of higher magnitude are more favourable in minimising energy usage for USV voyage with a no substantial increase in computational effort. This leads to the fact that proposed approach can assist USV in utilising the ocean environment intelligently to minimise energy usage by integrating current information with path planner.

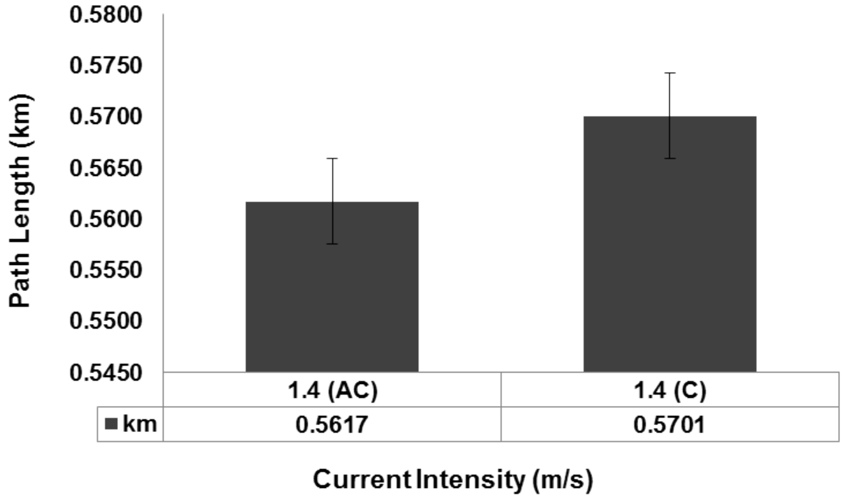


Figure 4.22: Comparison of path length obtained for currents moving with intensity of 1.4 m/s in anticlockwise (AC) and clockwise (C) directions. The interval on each bar denotes the standard deviation of the path length. Km represents Kilometer

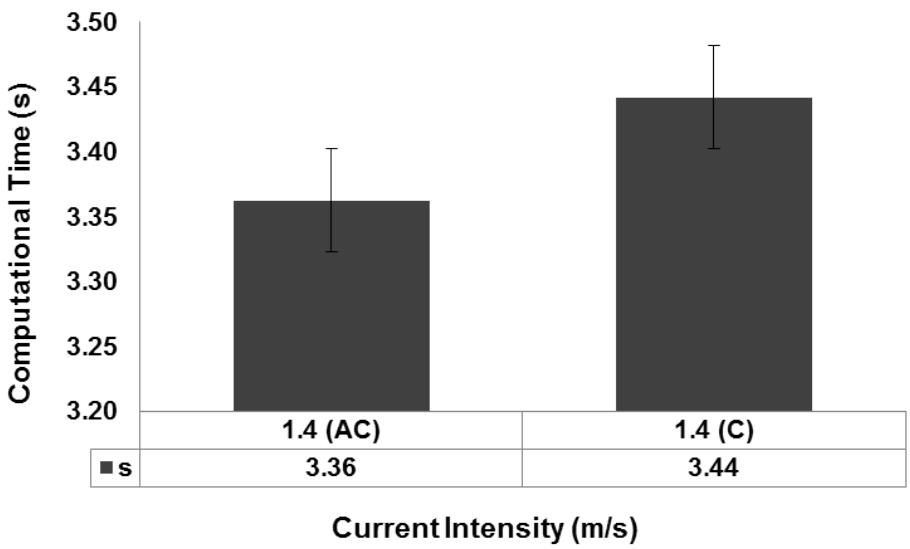


Figure 4.23: Comparison of computational time to determine path obtained for currents moving with intensity of 1.4 m/s in anticlockwise (AC) and clockwise (C) directions. The interval on each bar denotes the standard deviation of the computational time.

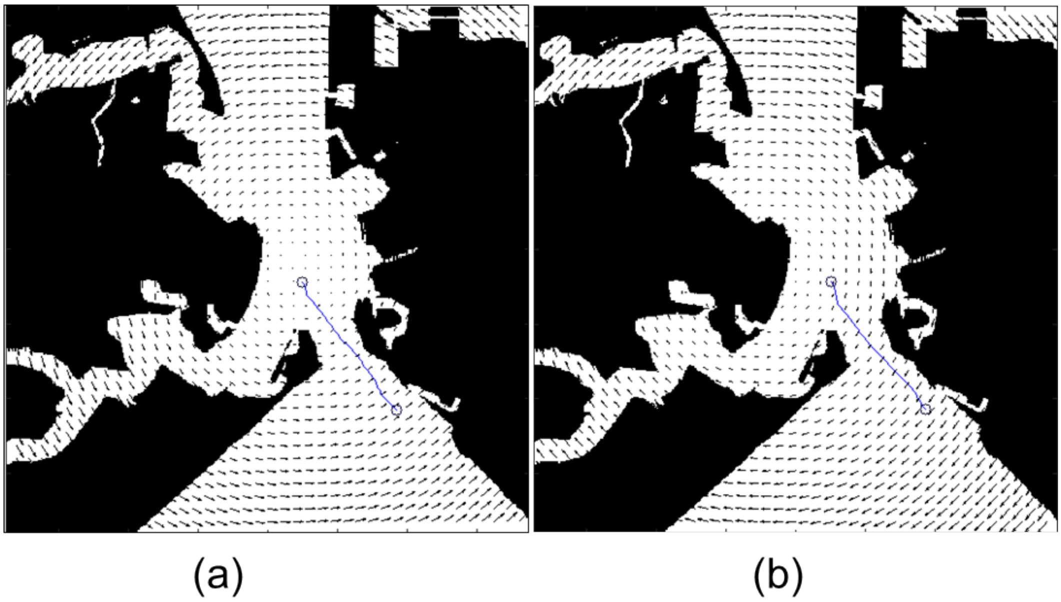


FIGURE 4.24: Comparison of paths obtained for currents moving with intensity of 2.5 m/s in (a) anti-clockwise and (b) clockwise direction. The start and goal states are same as shown in Figure 4.12. The safety distance constraint of 20 pixels is maintained for both scenarios.

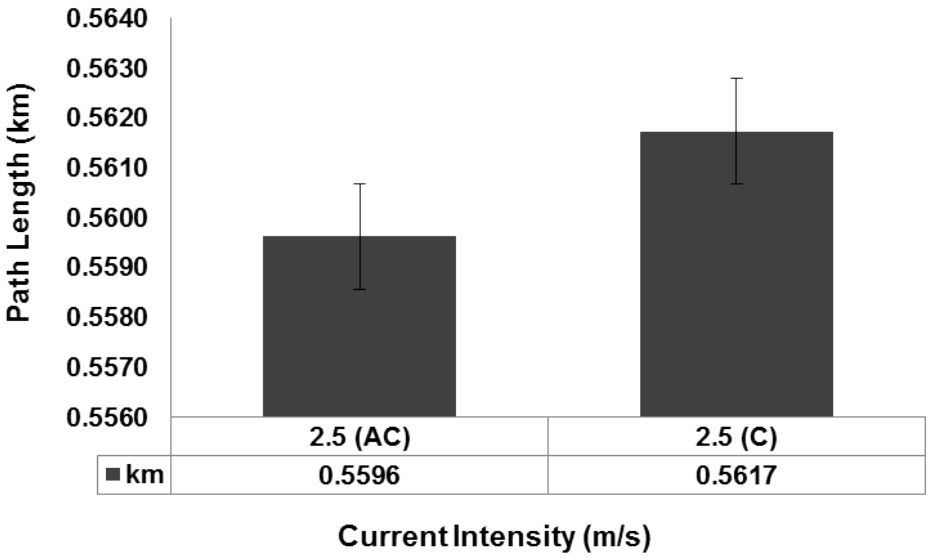


FIGURE 4.25: Comparison of path length obtained for currents moving with intensity of 2.5 m/s in anticlockwise (AC) and clockwise (C) directions. The interval on each bar denotes the standard deviation of the path length. Km represents Kilometer

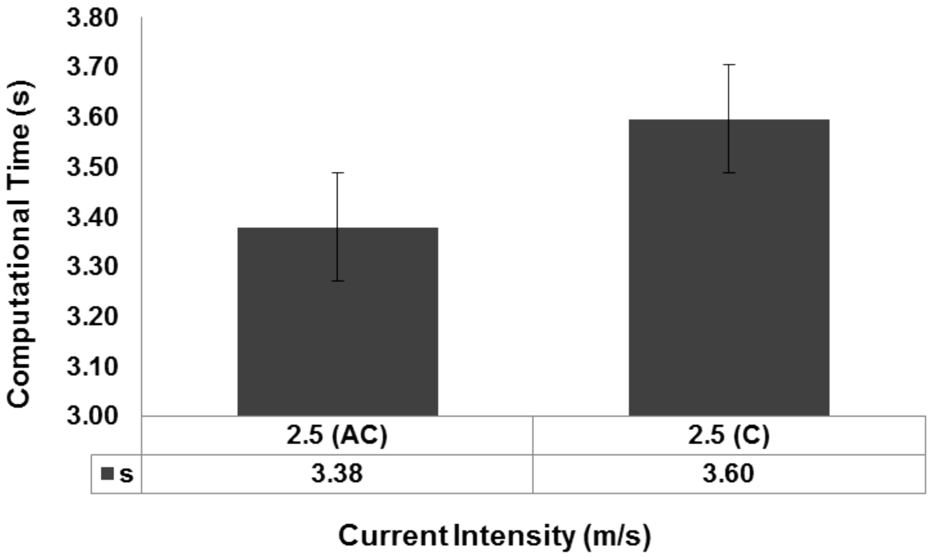
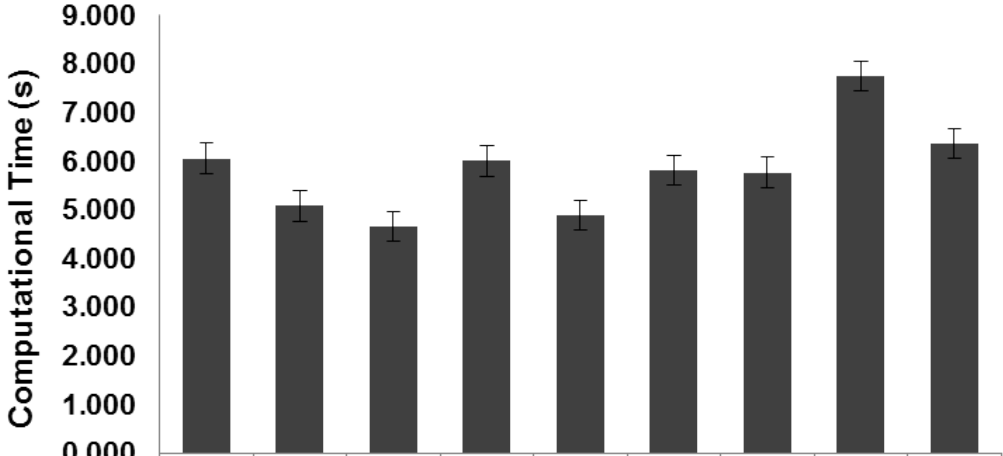


FIGURE 4.26: Comparison of computational time to determine path obtained for currents moving with intensity of 2.5 m/s in anticlockwise (AC) and clockwise (C) directions. The interval on each bar denotes the standard deviation of the computational time.

4.3.4 Constrained A* approach with single moving obstacle and environmental disturbance

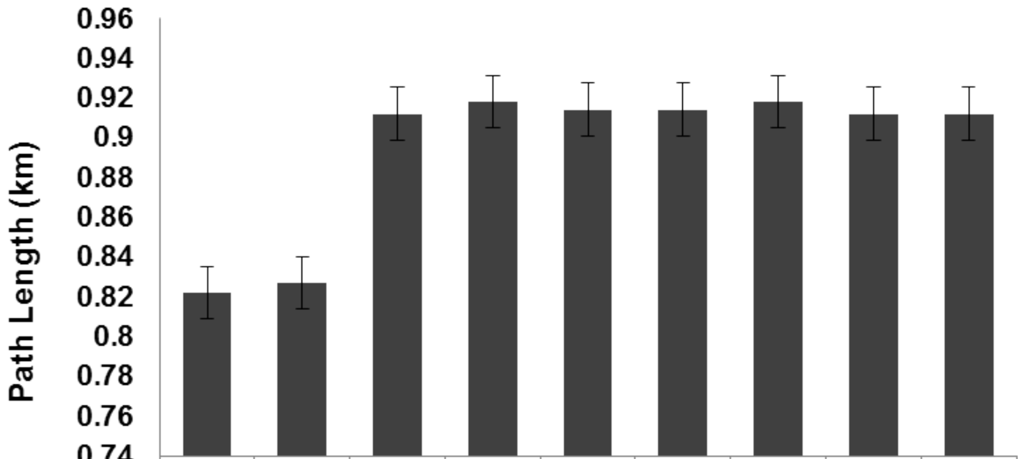
In order to create a more complete picture of the operational environment near to Portsmouth harbour and to analyse the effectiveness of the proposed approach in cluttered environment, a single moving obstacle is introduced in the map in presence of sea surface currents of moderate intensity as discussed in Section 4.3.3. Since the complexity of the environment has increased, a more flexible safety distance constraint of 15 pixel has been adopted for this study in order to keep a proper trade off between optimal way points and environmental complexity. Figure 4.28 shows the generated paths for different start time in the environment comprising of static obstacle, sea surface currents of 1.4 m/s moving in anti-clockwise direction and moving obstacle (where each dynamic position is considered static). Comparison of path length and computational time for all scenarios presented in Figure 4.28 are shown in Figure 4.27 and Figure 4.29 respectively.

From the results obtained, one can observe that as the obstacle approaches the safety domain of the USV, there is a increase in path length observed with a decrease in computational effort for cases (as found with mission start time of 30 seconds and 60 seconds), where, an increased path length is observed. In addition to that, most cases have been able to generate path within a reasonable computational time. These results show that the proposed algorithm can generate safer way points for the USV voyage for long and short duration missions in a cluttered complex environment.



	0	10	20	30	40	50	60	80	100
s	6.060	5.083	4.666	6.008	4.885	5.812	5.772	7.754	6.370

FIGURE 4.27: Comparison of computational time obtained for scenario with sea surface currents of 1.4 m/s moving in anti-clockwise direction having a moving obstacle for different start time of 0, 10, 20, 30, 40, 50, 60, 80 and 100 seconds. The interval on each bar denotes the standard deviation of the computational time.



	0	10	20	30	40	50	60	80	100
km	0.822	0.827	0.912	0.918	0.914	0.914	0.918	0.912	0.912

FIGURE 4.29: Comparison of path length obtained for scenario with sea surface currents of 1.4 m/s moving in anti-clockwise direction having a moving obstacle for different start time of 0, 10, 20, 30, 40, 50, 60, 80 and 100 seconds. The interval on each bar denotes the standard deviation of the path length. Km represents Kilometer

4.4 Concluding remarks

In this chapter, a constrained A* approach for optimal path planning of USVs in a confined maritime environment is proposed. The objective of generating safer way points by keeping a safe distance from the obstacle was evaluated in simulations, conducted

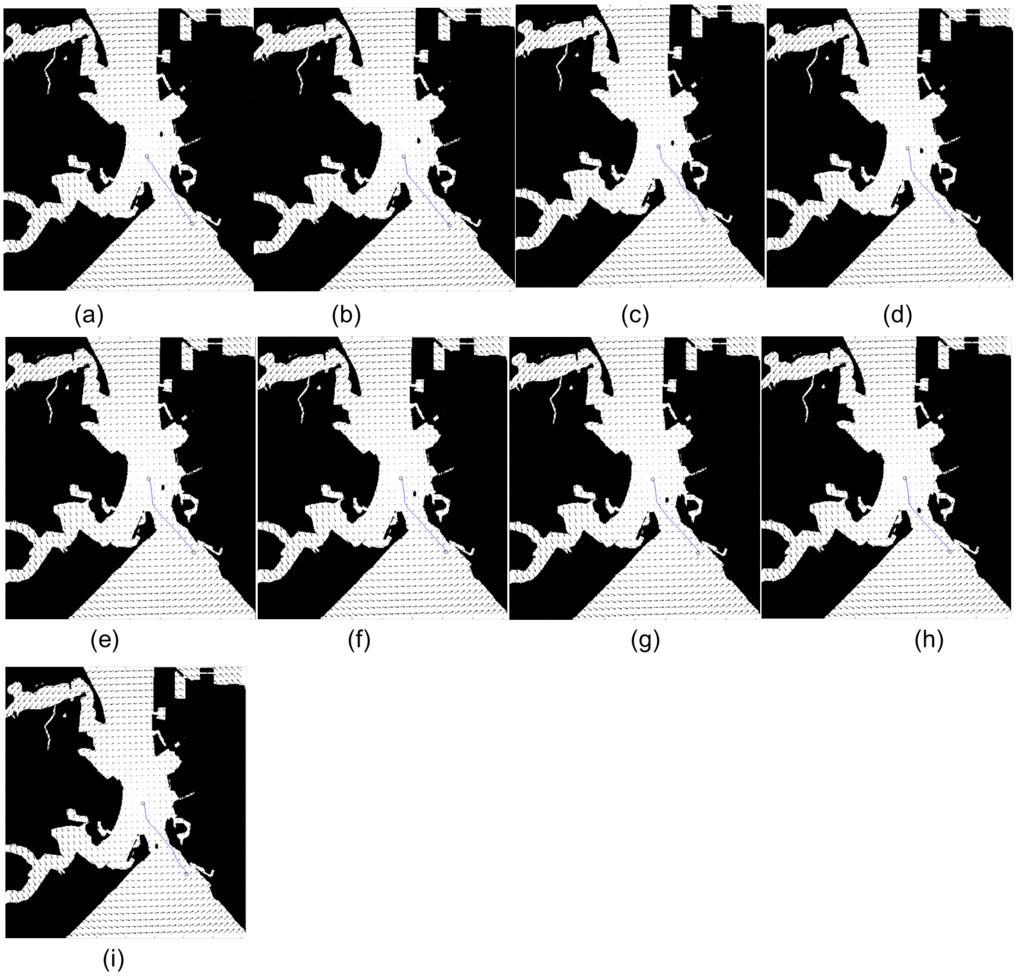


FIGURE 4.28: Comparison of paths obtained for scenario with sea surface currents of 1.4 m/s moving in anti-clockwise direction having a moving obstacle for different start time of (a) 0 (b) 10 (c) 20 (d) 30 (e) 40 (f) 50 (g) 60 (h) 80 (i) 100 seconds. The start and goal states are same as shown in Figure4.12. The safety distance constraint of 15 pixels is maintained for all scenarios.

in various environments comprising of static obstacle, moving obstacle and sea surface currents of different intensities. The upstream and effects of sea surface currents was evaluated and effect of sea surface currents with moving obstacle was also analysed.

The simulation results shows that the present approach generates safer way points for USV voyage in a computationally efficient manner against the conventional A* approach with no loss of optimality. The approach is found to be robust, computationally efficient and can be extended for real time path planning of USVs in confined water. In conclusion it is considered, such an optimal approach is suitable for global path planning of USVs.

Real world application of simulation studies needs hardware and software in loop implementation. Since the payload associated with USVs have limited computational capacity, the algorithm needs to be multi-threaded, implemented on Graphics Processing Unit, written in low level languages such as C++ and parallelized on on-board computers of the USV. Although the current algorithm has been written and simulated in C++, there is a need to multi-thread the current algorithm as well as a need to be implemented using Graphics Processing Unit for practical application

In order to extend the current work from a single vehicle to multi-vehicle system, there is a need to integrate the current path planner with a path follower approach and swarm integration approach to ensure that multi USVs can be navigated in a robust and effective manner in a maritime environment. The next chapter deals with this integration of the proposed path planner with a lower level guidance system based on virtual target approach integrated with a swarm aggregation algorithm based on attraction- repulsion strategy. The results of the current chapter has been published as a research article by the Ocean Engineering which is shown in Appendix B.

Chapter 5

Optimal Approach to Multi-USV Framework

"At sea, I learned how little a person needs, not how much"

Robin Lee Graham, Sailor

Efficient motion planning of multiple USVs in a dynamic maritime environment is an important requirement for increasing mission efficiency and achieving motion goals. This chapter outlines a range of techniques related to multi vehicle systems in different domains of aerial, ground and marine robots with a special attention on methods related to flexible formations to avoid collisions for multi vehicle systems. The current chapter then proposes a novel framework by integrating two approaches of intelligent path planning and virtual target path following guidance for a multi-agent USV framework to perform a coordinated and cooperative navigation of USVs in a constrained maritime environment. Also in the current chapter, a safety distance constrained A* approach produces an optimal, computationally efficient and collision free path which is later smoothed using a spline to provide an optimal trajectory as input for virtual target based multi-agent guidance framework to navigate multiple USVs. The virtual target approach provides a robust methodology of global and local collision avoidance based on known positions of vehicles. The combined approach is evaluated with a different number of USVs and in different environmental scenarios to understand the effectiveness of the approach from the perspective of practicality, safety and robustness.

5.1 Introduction

Motivated by the increased presence of autonomous agents, research organisations and industrial firms are putting their effort in the development of unmanned vehicles, able to operate autonomously in the marine environment. Current state of high-performance marine vehicles operating in marine environment were once just a figment of our imagination as a prototype tool. They are consolidated reality of today's maritime framework, employed in the most diverse array of applications ranging from reconnaissance in hostile areas to operations in dangerous weather conditions to name a few.

Substantial research has been conducted in the last two decade towards increasing autonomy of USVs, being the basis of the near-future autonomous ships. Moreover, a step further in the development of autonomous systems is the capability of operating in a team, so as to improve the overall system performance in terms of cost and safety. With this final objective of allowing a multi-USV agent team to navigate autonomously within a commercial route such as coastal area or an harbour, a number of problems have to be solved in order to provide the essential capabilities to the system to operate in an autonomous and safe manner. Formation control and cooperative motion planning are two major areas being investigated in the literature towards the study of the multi vehicle systems. A list of key factors that needs to be considered for designing algorithms related to formation control and cooperative motion planning are already listed in the Figure 1.2 with formation control being the most widely investigated area. It is quite evident from the Figure 1.2 that both research areas share a large number of key factors and there is a strong need to develop a hybrid approach combining the key features from both areas. However, it is most important to discuss details of different approaches associated with formation control and cooperative motion planning before delving into the details of the multi USV framework adopted in the current study.

The organisation of the current chapter is as follows. In section 5.2, an overview of the architecture of a multi vehicle system and a comprehensive comparison and analysis of the strategies associated with the multi vehicle system is explained. In section 5.4, the methodology adopted in the current study is described with concepts of basic path-following with multi vehicle coordination are described in the subsection 5.4.2 while in the section 5.5 results of coordinated vehicles motion are presented. Lastly, conclusions are reported in section 5.7.

5.2 Multi vehicle system and formation

The evolution of the concept of the cooperative behaviour of the multi vehicle system is inspired from the animal behaviour such as self organisation of ants or swarming of bees, where the formations help in the survival and evolution of the species (Dorigo and Gambardella (1997), Pham et al. (2006)). The initial effort in understanding the cooperative behaviour of multi vehicle systems inspired from the animal behaviour started in the 1980s leading to development of ACTor-based robots and equipment synthetic system (ACTRESS), a multi robot system architecture developed in Japan (Parker (2000)).

The initial real world application of the multi vehicle system started with the use of UGVs in disaster management followed by the deployment of their applications in area mapping and surveillance (Nagatani et al. (2011), Fox et al. (2006)). Later this advancement in the technology was extended in space research for the purpose of planetary exploration (Huntsberger et al. (2003)). With respect to multi UAV systems, a huge amount of research has happened over last two decades for a variety of applications including disaster management and environmental monitoring (Hayat et al. (2016),Yanmaz et al. (2018)) and is still an open research area.

In the research area of the marine robots where a good number of studies during the last decade have happened in the area of multi AUV system towards applications such as bathymetric surveys, ocean monitoring and data acquisition (Fiorelli et al. (2006), Cao et al. (2016)). In terms of a multi USV framework where the current thesis focuses on, fewer studies have taken place in the last decade with a focus on applications such as collaborative anti-submarine warfare, surveillance of territorial waters and underway ship replenishment (Peng et al. (2013), Panagou and Kyriakopoulos (2013)). It is worth noting from the literature that compared to the research on developing approaches for fleet of UGVs, UAVs and AUVs very fewer studies have taken place in the area of USV formations and there is a strong need to explore the area of cooperative behaviour with a multi USV framework. In fact, owing to the nature of the USV operations, an USV plays an important role in the large scale cross platform cooperation among different unmanned vehicles in the maritime environment as shown in Figure 5.1. This significance is quite evident from the recent defence reports published by UK and US Department of Defence (DoD)(US Military (2010),Royal Navy (2016)).

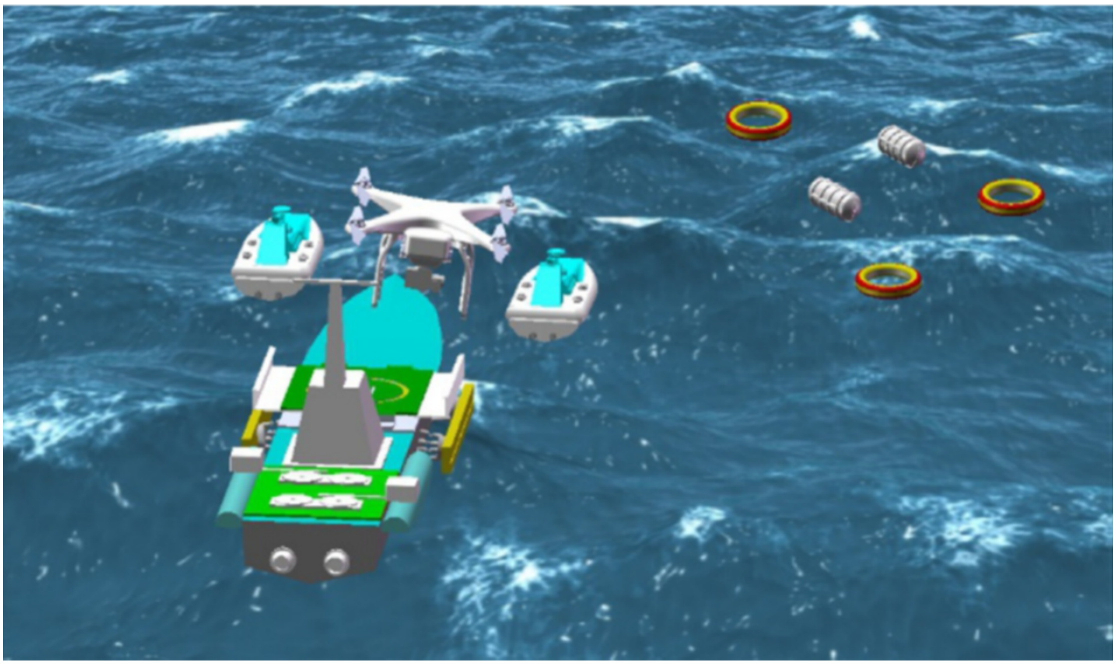


FIGURE 5.1: Schematic of the UAV and USV formation (Source: Ma et al. (2018))

5.2.1 Multi vehicle system architecture

Liu and Bucknall (2015) have proposed a generic architecture towards cooperative behaviour of a multi vehicle formation as shown in Figure 5.2 which comprises of three layers namely, task management , path planning and task execution. The task management layer takes care of the formation shape and formation allocation of the multi vehicle system based on the requirements of the mission i.e. improving the efficiency of the mission in terms of the spatial and temporal coverage. Towards the literature pertaining to the marine robots, the concept of self organising map (SOM) has been extensively used in the task management of the multi vehicle systems. Zhu et al. (2013) have used SOM towards dynamic task assignment and path planning of a multi AUV system in a three dimensional underwater environment along with the work of Huang et al. (2014) which used the approach of SOM to assign a team of AUVs to achieve multiple target locations in a dynamic ocean environment. With respect to USVs, the work of Liu and Bucknall (2018a) has used SOM approach integrated with FM based reactive method towards collision avoidance.

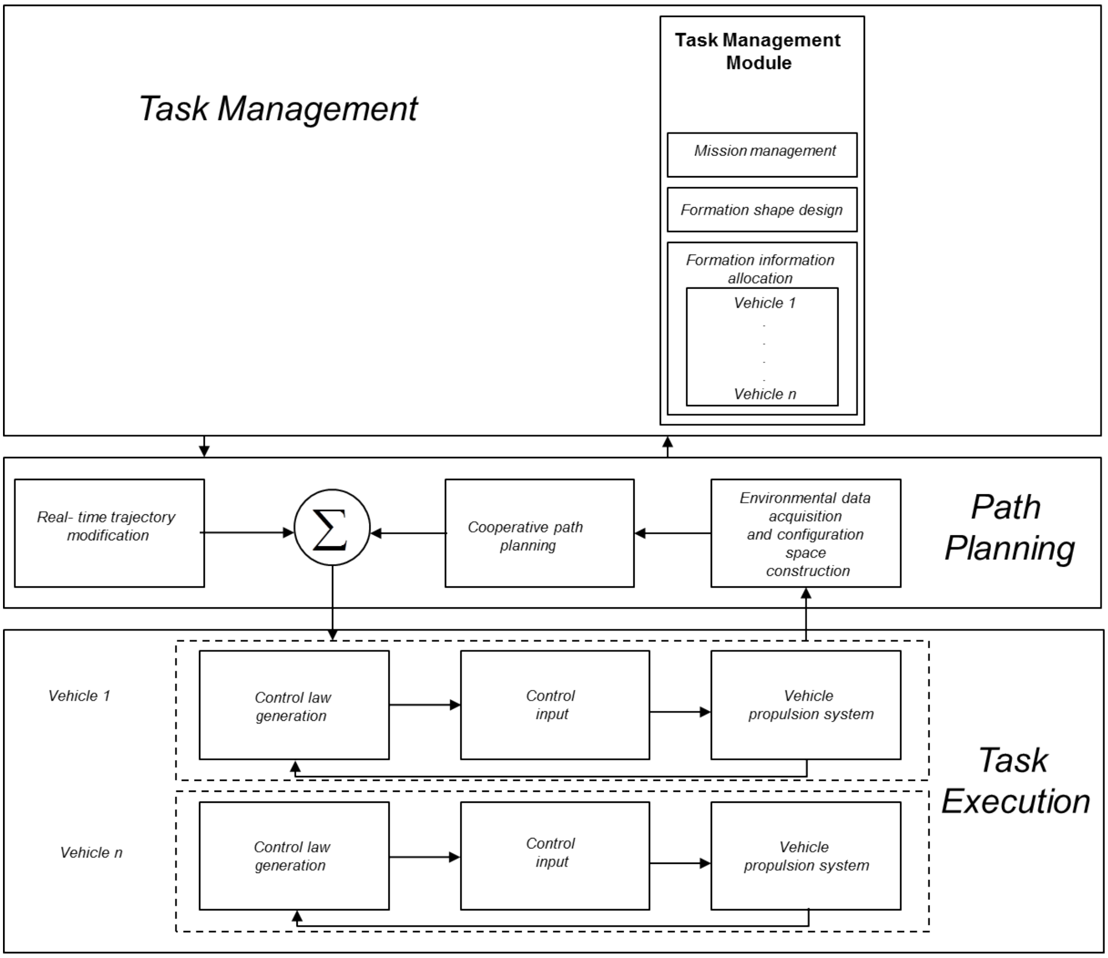


FIGURE 5.2: Generic architecture of a multiple vehicle system (Source: Modified from Liu and Bucknall (2018b))

Path planning layer is the second layer of the multi vehicle architecture which comprises of three components of environmental mapping, cooperative path planning and real time trajectory modification. A detailed survey towards path planning of single and multiple USVs has been explained in the Chapter 2.However, a number of recent studies needs a special mention in order to deal with real time trajectory modification and emergency situations. The work of Hinostroza et al. (2018), Rajendran et al. (2018), Singh et al. (2018), Wang et al. (2018a,b) have made an effort recently to integrate the task planning with dynamic constraints and a practical maritime environment to generate trajectories with practical applications.

Task execution takes generated paths as an input from the path planning module where dynamic variables of the vehicle i.e. velocity, position etc. are used in closed loop control systems to modify the trajectories of the fleet of vehicles in real time. Extensive details of the review papers associated with such marine control systems have already been mentioned in the Section 2.7.

5.2.2 Approaches associated with cooperative behaviour of multi vehicle systems

Two research approaches of formation control and cooperative path planning have been investigated to understand the cooperative behaviour of the multi vehicle system in the literature. A huge amount of research has been conducted in the area of autonomous vehicles over the last four decades in the area of formation control which can be found in the different review studies of Chen and Wang (2005b), Kanjanawanishkul (2016) and Guanghua et al. (2013b). With respect to the area of cooperative path planning, the studies related to the multi vehicle path planning of USVs have already been covered in the Section 2.9. The key factors associated with the formation control and cooperative path planning are listed in Figure 1.2. Projects within the European Union and United States are major examples of the development of multi vehicle framework for marine robots. It started with the CADRE system (Willcox et al. (2006)) project, where a network of AUVs and USVs were used to cooperate autonomously to conduct mine countermeasure using high accuracy navigation and a multi modal architecture. The same framework was extended in the Autonomous Ocean Sampling Network II (AOSN II) project (Bellingham and Chandler (2003)), where there is complete interconnection and cooperation of aerial, surface and underwater (including gliders) vehicles, with the aim of developing a heterogeneous and intelligent monitoring network. Another major milestone was the GREX project (Aguiar et al. (2009)), towards creation of a conceptual framework for heterogeneous swarm of robots working in cooperation to achieve mission goals optimally. The following section will make a discussion on the various formation control strategies, their comparison and their implementation in the area of marine robotics.

5.2.3 Formation control strategies

The basic classification of the approaches associated with the formation control are shown in Figure 5.3. Three important features of formation control i.e. shape forming, shape maintenance and shape variation are being compared for their compatibility with each method of the formation control while the criteria of stability and real time for each method is being scored with high and medium as shown in Figure 5.3. Each of these approaches has its own advantages and disadvantages and their implementation on marine robots is explained in the following subsections.

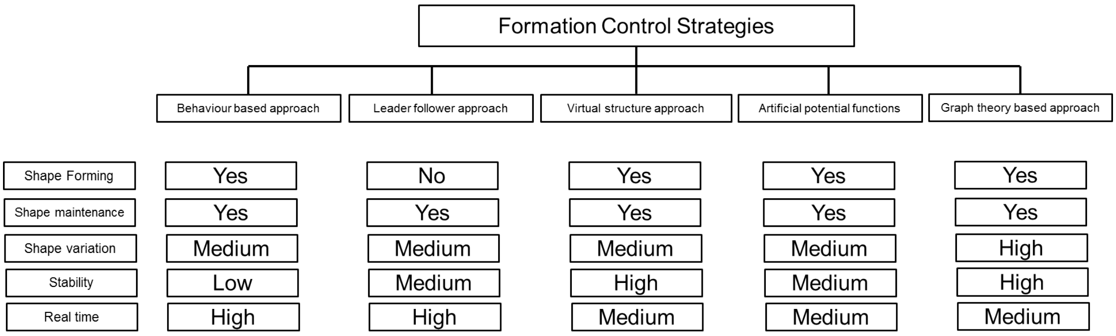


Figure 5.3: Comparison of formation control strategies (Source: Modified from Guanghua et al. (2013a))

5.2.3.1 Behaviour based approach

This approach is designed on the basis of the motion primitives associated with each robot such as obstacle avoidance, goal seeking and formation keeping where weighted sum of each of these primitives and interaction between robots is used to create motion patterns for multi vehicle systems. Sensor data is taken as input behaviour and output is send to robots behaviours which can be viewed together as a structured network of interacting behaviours. A module coordinator finally decides a set of behaviours used to control the robot. This approach was initially proposed in the area of mobile robotics by Balch and Arkin (1998) where a weighted sum of five behaviours namely, move to goal, obstacle avoidance, swirl, noise and formation keeping is used to control the formation of robots. With respect to USVs, the work of Arrichiello et al. (2006) used Null-Space-Based behavioural control (NSB) as guidance system aimed at guiding the fleet of surface vehicles in complex environment and simultaneously performing multiple tasks i.e. obstacle avoidance or formation keeping. The work of Benjamin et al. (2006) addressed the concept of COLREGs compliance navigation of two USVs using the concept of behavioural control and optimality and validated simulations using first in-field demonstration. The studies of Kumar and Stover (2000) and Rosenblatt et al. (2002) have covered the area of application of behavioral approach in the area of AUVs.

The parallel and distributed communication among vehicles with less information being shared makes this approach advantageous for real time application although difficult mathematical formulation and unwarranted convergence are a few drawbacks associated with this approach.

5.2.3.2 Leader-follower approach

The leader follower approach works on the principle of few robots considered as leaders while the others act as followers where followers track the position and heading of the leader to some predefined temporal and spatial offset. A schematic of two robots using a basic leader follower controller is shown in the Figure 5.4.

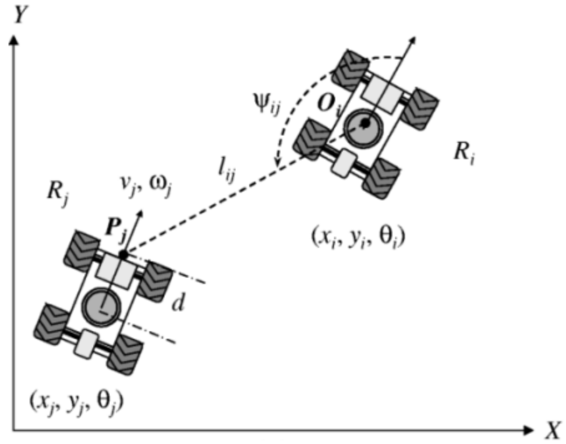


FIGURE 5.4: Two robots using basic leader-following controller (Source: Das et al. (2002))

Two popular feedback control methods as proposed by Das et al. (2002) are being used in this approach namely, $l-\phi$ control and $l-l$ control. The $l-\phi$ control method is used to maintain a desired relative distance l_{ij} and a desired relative heading ψ_{ij} between two robots as shown in Figure 5.4 while the $l-l$ method is used to maintain the desired relative distance between three robots i.e. l_{23} and l_{13} as shown in Figure 5.5.

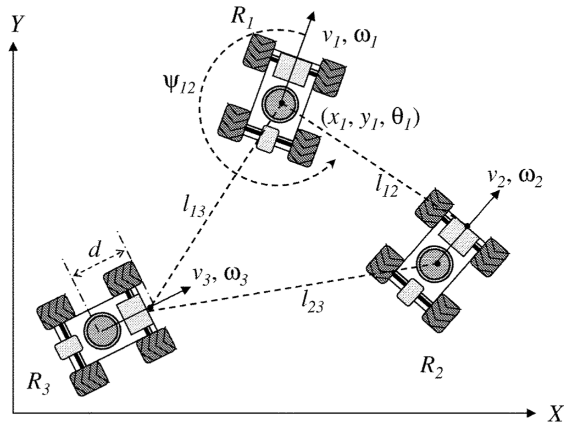


FIGURE 5.5: Three robots using basic leader-following controller (Source: Das et al. (2002))

This scheme has been much preferred in understanding the cooperative behaviour of marine vehicles due to its simplicity and scalability. During the last decade, a good number of studies like Skjetne et al. (2002), Breivik et al. (2008), Peng et al. (2011), Jin (2016) and Liu and Bucknall (2016b) have adopted a leader-follower framework in formation control of multiple USVs in which different techniques like non linear control, integrator backstepping, sliding mode control, Lyapunov backstepping and angular FM have been used respectively. Towards understanding the cooperative behaviour of AUVs, leader-follower approach has been used in the work of Cui et al. (2009, 2010), Edwards et al. (2004), Li and Wang (2013), Peng et al. (2015), Rout and Subudhi (2016), Xing et al. (2017), Yang and Gu (2007) through adoption of different control techniques for the formation control of multiple AUVs.

This approach is entirely determined by the trajectory of the leader which simplifies the problem of formation control to a tracking control. The followers follow the leader based on the WiFi communication between leader and followers. The WiFi communication is responsible for the sharing of velocity and position data between followers and leader based on which formation control approaches operate. However, a major drawback of this approach is that formation does not accept leader faults and in case of absence of a leader, a complete formation needs to be redefined.

5.2.3.3 Virtual structure approach

This approach considers the complete formation as a rigid body where the whole formation is considered as a virtual structure. The dynamics of a single vehicle is translated into a desired motion of each robot in the virtual structure and robot positions are updated according to the local or global path planner. The approach was initially proposed by Tan and Lewis (1996b) and a schematic of the approach is shown in Figure 5.6.

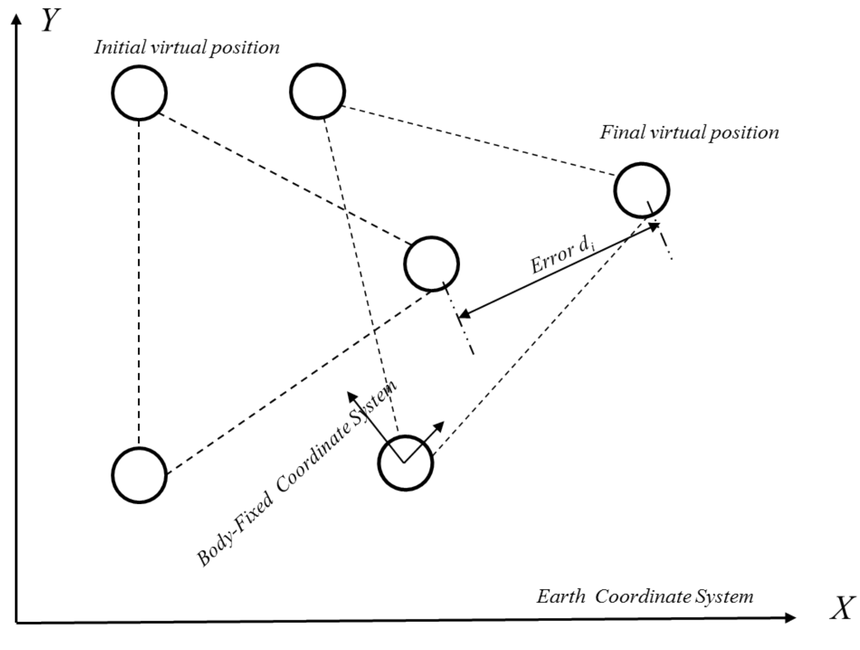


FIGURE 5.6: Schematic of the virtual structure approach for a three robot framework

The approach comprises of four major steps as follows:

1. Define the dynamics of the virtual structure and align the virtual structure with the initial positions of the robot.
2. Define the heading of the virtual structure.
3. Compute the individual trajectory for each robot from the start to the goal point as the corresponding robot contribute to an error of d_i as shown in Figure 5.6.
4. Adjust the velocity of each robot to follow the desired trajectory closely, in addition to, maintaining the geometry of the virtual structure.

A good number of studies have been conducted in the area of mobile and aerial robotics using a virtual structure approach (Lewis and Tan (1997), Mehrjerdi et al. (2011), Ren and Beard (2004)) while the work of Do (2012) covers the area of formation control of underactuated ships using a virtual structure approach. Despite its high fault tolerant capability, this approach suffers from lack of flexibility and high computational cost in a complex operational environment.

5.2.3.4 Artificial potential function

The concept was initially proposed by Khatib (1986) and is explained in the Section 3.2.1. This approach has been quite popular in the last decade in the formation control of multi robots systems and is quite evident from the work of Zhang et al. (2010), Ge and Fua (2005), Paul et al. (2008) and Wang et al. (2006). In the area of marine robotics, some recent work in the application of artificial potential function towards formation control can be found in Huang et al. (2017), Das et al. (2016), Mei and Arshad (2015) and Zhai et al. (2013).

This approach can be applied in real time but suffers from the issues of local minima.

5.2.3.5 Graph theory based approach

In this approach, kinematic or dynamic properties of the robots are expressed as nodes of a graph with edges representing constraints between the robots. Under this approach, control theory and dynamical systems theory is applied in combination with graph theory to study the formation controller and its stability. Many recent studies of Liu and Tian (2009), Ren (2006) and Krick (2007) have used the communication network based control strategy, consensus based control strategy and stop-and-go strategy respectively to understand the formation control using graph theory. This method can represent any formation using graph although simulation hitherto remains a major drawback.

5.2.4 Concluding remarks on formation control strategies

The aforementioned section reviews the current state-of-the-art on the strategies associated with the formation control towards comprehending the cooperative behavior of the marine robots. There are certainly other approaches in the formation control that are not discussed in detail here but from the discussion it is quite evident that a hybrid strategy for the multi USV system is the trend of the future. A hybrid approach is a mix of stability and formation behavior where in an open space a stable virtual leader based approach can be used while in complex environment more behaviour based characteristic takes over the control. The next section explains the methodology adopted in the current thesis towards development of a hybrid framework for a multi USV system.

5.3 Major contributions of the current study

The current study extends the work of Bibuli et al. (2014) through the incorporation of three major characteristics within the existing framework of Bibuli et al. (2014) which are as follows:

1. The current work incorporates the practical maritime environment of Portsmouth harbour within the existing framework of Bibuli et al. (2014) where an open sea environment has been considered comprising of no static obstacles.
2. The current work extends the framework of Bibuli et al. (2014) by incorporating the feature of external collision avoidance with shoreline by modelling shoreline as a set of repulsive points using a repulsive potential function.
3. The existing framework of Bibuli et al. (2014) considers a random polynomial trajectory as a reference trajectory for navigating the swarm of USVs. The current work incorporates an optimal and computationally efficient path within the existing framework of Bibuli et al. (2014) for navigating the swarm of USVs.

5.4 Methodology

The current study adopts a two layered approach towards the multi-USV framework problem. In the higher level of the hierarchy, a robust path planner based on a constrained A* approach is adopted to generate optimal waypoints, which are later smoothed using a polyfitting operation. This smoothed trajectory is given as an input to a lower level guidance system based on a virtual target approach integrated with a swarm aggregation algorithm based on an attraction- repulsion strategy. Figure 5.7 shows a schematic of the methodology adopted in the present chapter.

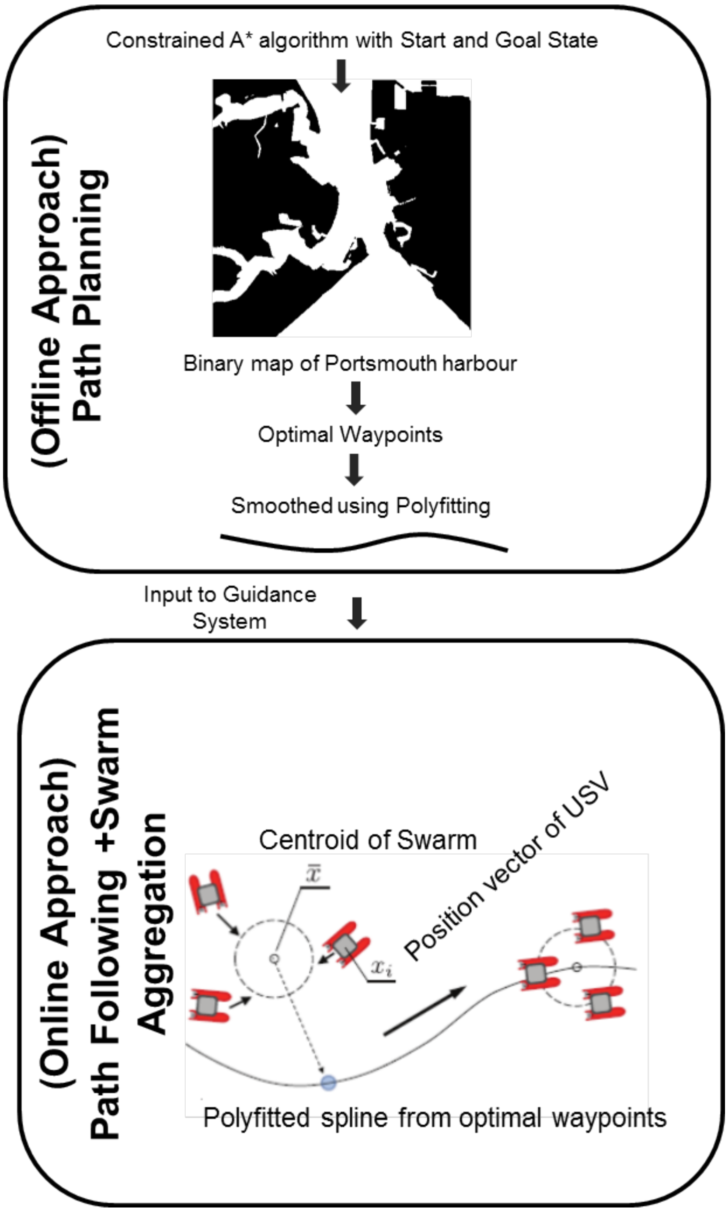


FIGURE 5.7: Schematic of integrated path planning, guidance system and swarm aggregation approach

A constrained A* approach as described in the previous chapter with a safety distance of 20 pixels being chosen to generate optimal waypoints in a constrained channel of Portsmouth harbour. A zigzag trajectory is produced from the waypoints generated from the proposed approach. The chosen waypoints for smoothed trajectory are tabulated in Table 5.1. The waypoints are chosen so that complexity of the navigation in a constrained harbour is accounted in an offline approach. The generated trajectory from the safety distance constrained A* approach and smoothed trajectory from chosen waypoints are shown in Figure 5.8.

TABLE 5.1: Chosen optimal waypoints (WP) from path planner

	Start	WP 1	WP 2	WP 3	Goal
x (pixels)	238	261	272	285	299
y (pixels)	212	251	271	284	312

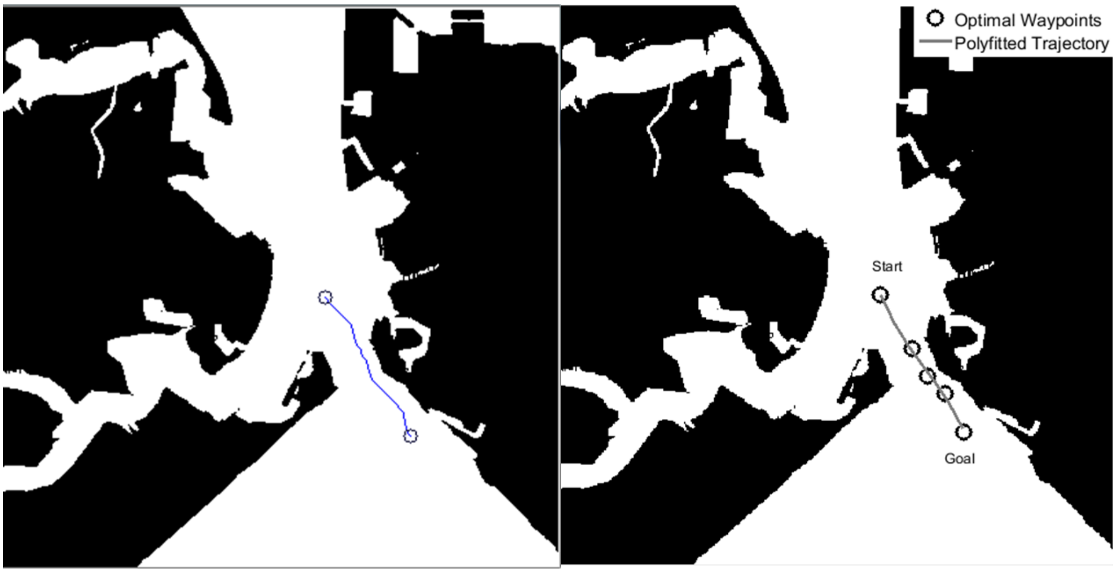


FIGURE 5.8: Generated (left) and smoothed trajectory (right) from the optimal waypoints produced by the path planner. Binary map of 800 x 800 resolution is considered for the current study with one pixel representing 3.6 m on a real map

The chosen waypoints are fitted to a polynomial parameterised in terms of $\gamma \; \forall \; \gamma \in \left[0{,}61\right]$. Parametric equations, $P_d(\gamma)$ used as an input towards online approach of path following and swarm aggregation are shown in Eq. 5.1.

$$P_d(\gamma) = \begin{cases} x(\gamma) = \gamma + 238, \\ y(\gamma) = -0.000325(\gamma + 238)^3 + 0.2637(\gamma + 238)^2 \\ .. - 72.5508(\gamma + 238) + 6505 \end{cases} \tag{5.1}$$

5.4.1 Preliminaries related to multi vehicle path following

In this thesis, the swarm as defined by Gazi and Passino (2003) composes of a set X of n robots, each one characterised by the vector $x_i(t) \in \mathbb{R}^m$ with $i = 1, ..., n$ in Cartesian coordinates on a 2D plane. The instantaneous barycentre of the swarm is defined as $\tilde{x}(t) = 1/n \sum_{i=1}^{n} x_i i(t)$ and the vector distance of each robot from the centre is defined as $\epsilon_i(t) = x_i(t) - \tilde{x}(t)$. The collection of all robots and their distances from the barycentre is defined as $X(t) = [x_1(t).......x_n(t)]$ and $\epsilon(t) = [\epsilon_1(t).......\epsilon_n(t)]$.

The proximity graph $G_i = \{V, E\}$, where $V = \{v_i : i = 1, ..., n\}$ is the set of robots while the $E = \{\epsilon_{ij}\}$ is the set of edges representing communication channel between the robots and the centre, defines the interaction among the robots. The communication channel exists if the agents i and j are within the visibility range R_{ij} i.e. $\|x_i - x_j\| \leqslant R_{ij}$ with unidirectional communication from node i to node j. The Laplacian matrix associated with this graph G is defined as $L(G_i) = \Delta(G_i) - A(G_i)$, where the $A(G_i)$ is the adjacency matrix of $n \times n$ elements whose generic element $a_{ij} = 1$ if $i \neq j$ and $\epsilon_{ij} \in E$ and $a_{ij} = 0$ otherwise while $\Delta(G_i)$ is the degree diagonal matrix of

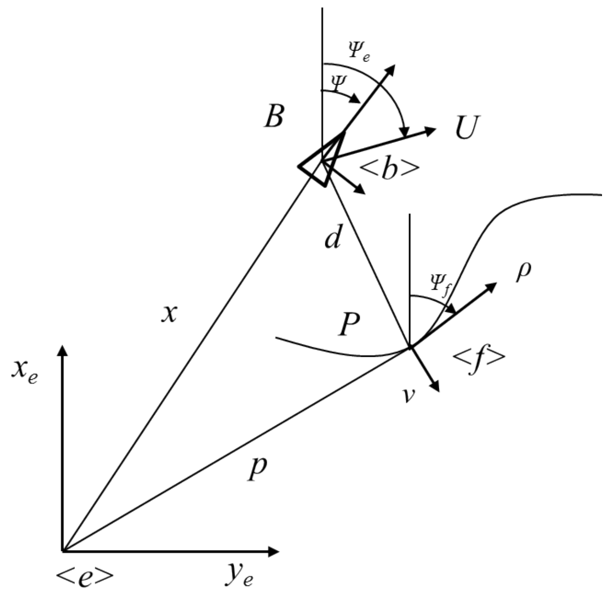


FIGURE 5.9: Frame definitions for path following algorithm based on a virtual target approach

$n \times n$ elements whose elements are $\Delta_i(G_i)$ i.e. degree of the node i. This matrix is a weak diagonal symmetric matrix where sum of rows and sum of columns is equal to zero.

The current chapter takes into account the idea of guiding a complete swarm of USVs through an instantaneous barycentre of swarm acting as a virtual target that moves along the reference path where following assumptions are required :

1. Onboard GPS is continuously measuring position of each USV in the swarm with reference to a common reference frame.
2. WiFi systems are providing a reliable data exchange needed to support inter-robot decentralised communication for position data sharing.

In order to achieve the above mentioned idea, a proper velocity is computed and imposed to the swarm aggregation algorithm, which in turn drive the motion of each USV in the USV swarm according to such reference velocity.

5.4.2 Path following algorithm

A graphical representation of the USV kinematics adopted in the current study for development of the path following algorithm is given in Figure 5.9. In general, two reference frames namely, Earth fixed reference frame $< e >$, where position and orientation $[x\ y\ z\ \Psi]^T$ of the USV is expressed and the body fixed reference frame $< b >$, where the relative surge and sway velocity $[u_r\ v_r]^T$ of the USV with respect to the water and yaw rate r are used to define the kinematics in the $< e >$ frame as follows (Bibuli et al. (2009)) :

$$\begin{aligned} \dot{x} &= u_r \cos\Psi - v_r \sin\Psi + \dot{x}_c \\ \dot{y} &= u_r \sin\Psi + v_r \cos\Psi + \dot{y}_c \\ \dot{\Psi} &= r \end{aligned} \tag{5.2}$$

where $[\dot{x}_c\ \dot{y}_c]$ denotes the sea current which is supposed to be irrotational and constant. Assuming that USV is moving with a constant surge with respect to the water with negligible sway, i.e. $v_r = 0$ and $\dot{u}_r = \dot{v}_r = 0$, the kinematic model represented in the Eq. 5.2 can be rewritten as follows :

$$\begin{aligned} \dot{x} &= U \cos\Psi_e \\ \dot{y} &= U \sin\Psi_e \\ \dot{\Psi}_e &= r\left[\tfrac{u_r^2}{U^2} + \tfrac{u_r}{U}(\dot{x}_c \cos\Psi + \dot{y}_c \sin\Psi)\right] = r\eta(t) \end{aligned} \tag{5.3}$$

where
$U = \sqrt{\dot{x}^2 + \dot{y}^2}$
$\Psi_e = \arctan\frac{\dot{y}}{\dot{x}}$

denotes the resultant velocity and orientation of the USV in $< e >$. The current work uses the concept of Serret-Frenet frame $< f >$ which moves along the reference path followed by the virtual target vehicle and tracked by the real vehicle. With reference to Figure 5.9, a point P with position vector $P = [x_p\ y_p\ 0]^T$ is defined in respect to $< e >$ frame. The point B, attached to the USV is expressed as $[s_1\ y_1\ 0]^T$ in $< f >$ frame. The rotational matrix to transform the parameters from $< e >$ to $< f >$ is defined in terms of Ψ_f as follows :

$$R = \begin{bmatrix} \cos\Psi_f & \sin\Psi_f & 0 \\ -\sin\Psi_f & \cos\Psi_f & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Assuming $r_f = \Psi_f$ and defining s as the signed curvilinear abscissa along the path, following expressions hold:

$$r_f = \dot{\Psi}_f = c_c(s)\dot{s} \quad ; \quad \dot{c_c(s)} = g_c(s)\dot{s}$$

where, $c_c(s)$ and $g_c(s) = dc_c(s)/ds$ denotes the path curvature and its derivative respectively. The velocity of P in the $< f >$ frame is defined as:

$$\left(\frac{dp}{dt}\right)_f = \begin{bmatrix} \dot{s} \\ 0 \\ 0 \end{bmatrix}$$

The velocity of B in the $< e >$ frame is defined as:

$$\left(\frac{dx}{dt}\right)_e = \left(\frac{dp}{dt}\right)_e + R^{-1}\left(\frac{dd}{dt}\right)_f + R^{-1}([0 \quad 0 \quad r_f]^T \times d)$$

where, d is the position vector from P to B. The velocity of B in the $< f >$ frame is obtained by multiplying the above equation with R and is as follows :

$$\left(\frac{dx}{dt}\right)_f = R\left(\frac{dx}{dt}\right)_e = \left(\frac{dp}{dt}\right)_f + \left(\frac{dd}{dt}\right)_f + [0 \quad 0 \quad r_f]^T \times d \qquad (5.4)$$

Based on the following relations

$$\left(\frac{dx}{dt}\right)_e = \begin{bmatrix} \dot{x} \\ \dot{y} \\ 0 \end{bmatrix}$$

$$\left(\frac{dd}{dt}\right)_f = \begin{bmatrix} \dot{s_1} \\ \dot{y_1} \\ 0 \end{bmatrix}$$

and

$$[0 \quad 0 \quad r_f]^T \times d = \begin{bmatrix} 0 \\ 0 \\ c_c(s)\dot{s} \end{bmatrix} \times \begin{bmatrix} \dot{s_1} \\ \dot{y_1} \\ 0 \end{bmatrix} = \begin{bmatrix} -c_c(s)\dot{s}y_1 \\ c_c(s)\dot{s}s_1 \\ 0 \end{bmatrix}$$

Eq. 5.4 can be rewritten as

$$R\begin{bmatrix} \dot{x} \\ \dot{y} \\ 0 \end{bmatrix} = \begin{bmatrix} \dot{s}[1 - c_c(s)y_1] + \dot{s_1} \\ \dot{y_1} + c_c(s)\dot{s}s_1 \\ 0 \end{bmatrix}$$

Solving for $\dot{s_1}$ and $\dot{y_1}$ gives

$$\dot{s_1} = [\cos\Psi_f \quad \sin\Psi_f]\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} - \dot{s}(1 - c_c y_1)$$

$$\dot{y_1} = [-\sin\Psi_f \quad \cos\Psi_f]\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} - c_c\dot{s}s_1 \qquad (5.5)$$

Replacing the top two equations in Eq. 5.5 and introducing the variable $\beta = \Psi_e - \Psi_f$, the final kinematic model in terms of the $< f >$ frame are as follows:

$$
\begin{aligned}
\dot{s_1} &= -\dot{s}(1 - c_c y_1) + U\cos\beta \\
\dot{y_1} &= -c_c \dot{s} s_1 + U\sin\beta \\
\dot{\beta} &= r_e - c_c \dot{s}
\end{aligned}
\tag{5.6}
$$

where $r_e = \dot{\Psi}_e = r\eta(t)$

Following the geometrical and kinematical analysis carried above, the distance error model, expressed with respect to the frame $< f >$, has the following form (Bibuli et al. (2009)):

$$
\begin{cases}
\dot{\rho} = (c_c\,\nu - 1)\,\dot{s} + U\cos\beta \\
\dot{\nu} = -c_c\,\dot{s}\,\rho + U\sin\beta
\end{cases}
\tag{5.7}
$$

In order to solve the path-following problem for a single-vehicle system, the aim is to develop a proper approach angle function Ψ^*, designed to reduce the linear error components (ρ and ν) to zero. The desired angle Ψ^* is a function of the cross-track error ν summed with the local path tangent, thus $\Psi^* = \Psi_f + \varphi(\nu)$, where the function $\varphi(\nu)$ is required to satisfy the following constraints:

$$
|\varphi(\nu)| < \frac{\pi}{2} \quad ; \quad \nu\varphi(\nu) \leq 0 \quad ; \quad \varphi(0) = 0
$$

Relying on a low level PI controller, providing an auto-heading regulator capable of tracking desired orientation profiles, it can be stated that considering the candidate Lyapunov function $V_\psi = \frac{1}{2}(\psi - \psi^*)^2$, the low level controller provides a behaviour such that $\dot{V}_\psi \leq 0$, i.e. the vehicle orientation converges to the desired angle $\psi \rightarrow \psi^*$ and it can be rewritten as $\beta \rightarrow \varphi(\nu)$. Moreover it is worth noticing that when $\dot{V}_\psi = 0$, an invariant set is defined, in which the condition $\beta = \varphi(\nu)$ holds. The task of the path-following controller design is achieved by the definition of the Lyapunov function $V = \frac{1}{2}(\rho^2 + \nu^2)$; computing the time derivative of the function V, the following expression is obtained:

$$
\dot{V} = \rho\dot{\rho} + \nu\dot{\nu} = -\rho\dot{s} + \rho U\cos\beta + -\nu U\sin\beta = \dot{V}_\rho + \dot{V}_\nu
$$

substituting $\dot{\rho}$ and $\dot{\nu}$ with the equation system (5.7) and defining $\dot{V}_\rho = -\rho\dot{s} + \rho U\cos\varphi(\nu)$ and $\dot{V}_\nu = -\nu U\sin\varphi(\nu)$.

The speed of the reference frame $\dot{s}$, i.e. the velocity of the virtual target moving along the path, can be used as an additional control variable. Imposing

$$
\dot{s}^* = K_\rho\rho + U\cos\beta \tag{5.8}
$$

as the desired virtual target speed, where K_ρ is a tunable controller parameter, the function $\dot{V}_\rho$ assumes the negative form $\dot{V}_\rho = -K_\rho\nu^2 \leq 0$. About $\dot{V}_\nu$, recalling the above-mentioned assumption on the attraction to the invariant set defined by $\dot{V}_\psi = 0$, β can be substituted by $\varphi(\nu)$, obtaining $\dot{V}_\nu = \nu U \sin\varphi(\nu)$. Selecting the function $\varphi(\nu)$ as

$$\varphi(\nu) = -\psi_a \tanh(K_\nu \nu) \tag{5.9}$$

with K_ν as a tunable controller parameter and ψ_a the maximum approach angle with respect to the local tangent ψ_f, the term $\nu U \sin\varphi(\nu)$ is ≤ 0 because of the assumption made on the function $\varphi(\nu)$. Being the terms $\dot{V}_\rho$ and $\dot{V}_\nu \leq 0$, thus entailing $\dot{V} \leq 0$, the global asymptotic stability for the path-following guidance system is proven.

5.4.3 Vehicle Coordination

The goal of coordinating an USV team to converge to and maintain a motion configuration, while at the same time moving along a desired reference path is realised through the definition of the following control input:

$$\dot{x}_i = u_i^s + u^g \tag{5.10}$$

where the term u_i^s, different for each USV, is the control effort required to reach a collective behavior while the term u^g, common to all the USV, refers to the expected trajectory of the fleet centroid, computed with reference to section 5.4.2 as:

$$u^g = \begin{bmatrix} u^* \cos\psi^* \\ u^* \sin\psi^* \end{bmatrix} \tag{5.11}$$

where u^* is the desired speed for the formation along the path and ψ^* is the reference guidance angle computed by the path-following module.
Considering a swarm composed of n robots, the following aggregation dynamics for each robot i is given:

$$u_i^s = \sum_{j \neq i} g(x_i - x_j) \tag{5.12}$$

where $g(\cdot)$ is the interaction function representing the function of attraction and repulsion between neighbouring robots. In particular, $g(\cdot)$ is defined as:

$$g(y) = -y\ [g_a(\|y\|) - g_r(\|y\|)]\,, \quad \forall\, y \in \mathbb{R}^m. \tag{5.13}$$

where $g_a(\cdot)$ is the attractive function and $g_r(\cdot)$ is the repulsive contribution, constrained by the following assumptions:

$$\begin{aligned} g_a(\|x_i - x_j\|) &\geq \alpha \\ g_r(\|x_i - x_j\|) &\leq \frac{\beta}{\|x_i - x_j\|^2} \end{aligned} \tag{5.14}$$

In order to maintain a practical equilibrium between the swarm formation term u_i^s and the path-following guidance term u_g, the u_i^s component is modified as follows:

$$\dot{x}_i = k_{sat} \frac{\sum_{j \in \mathcal{N}_i(t)} g(x_i - x_j)}{1 + \left\| \sum_{j \in \mathcal{N}_i(t)} g(x_i - x_j) \right\|}, \tag{5.15}$$

where $k_{sat} > 0$ is the saturation gain.

The stability of the overall system, originated by the interconnection between the path-following and swarm aggregation modules, is added in the Appendix A.

5.5 Simulation results

In order to ensure that complexity of the multi-USV operation in a constrained maritime environment is captured, this section reports results of three and four vehicles performing swarm aggregation and path-following from a randomly generated initial formation towards a reference path generated from proposed path planner. Figure 5.10 and Figure 5.13 shows the aggregation behaviour combined with motion against the reference path for three and four USVs respectively. Initial, intermediate and final positions of the formation are shown in Figure 5.10 and Figure 5.13. The reported results account for external collision with the shoreline into swarm evolution through attractive and repulsive functions introduced in Bibuli et al. (2014). The path-following module parameters are set to

$$K_\rho = 1.0,\ K_\nu = 0.8, \text{ and } \psi_a = \pi/3$$

Collision avoidance with the shoreline is simply implemented by considering the shore profile as a set of repulsive fixed points which, within a certain distance, concur in the vehicle motion evolution. The repulsive function $f(x)$ used to define the shoreline is $f(x) = -(5\eta - d_1)/d_1$, where d_1 is the Euclidean distance between the robot and the shoreline $\|x_i - x_{shoreline}\|$. The motion of the vehicles with respect to mutual agent interactions and to distance from the shoreline can be varied acting on the parameters of the attractive and repulsive functions. For all simulations, the values of the attraction and repulsion function parameters are set to $\alpha = 0.2$, $\beta = 1.2$ and $\eta = 3$. Figure 5.11 and Figure 5.14 shows the reference velocity profile for three and four USVs respectively, where velocity of the i-th robot is $\|\dot{x}_i\|$.

Regarding the velocity profiles, two main issues have to be discussed:

1. The oscillations in the required velocity of each USVs is due to the swarm aggregation functions; the oscillatory behaviour can be reshaped by different definition of attraction/repulsion functions.

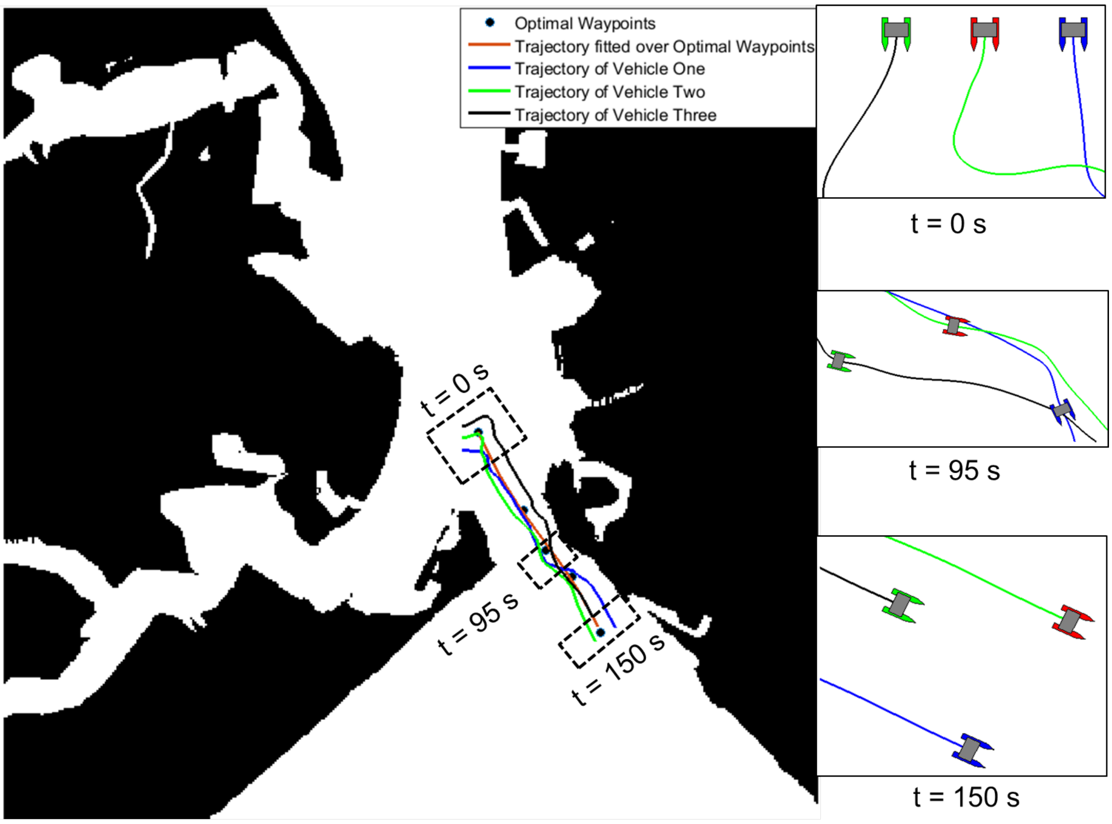


FIGURE 5.10: USV motions during swarm aggregation combined with path-following guidance for three USVs

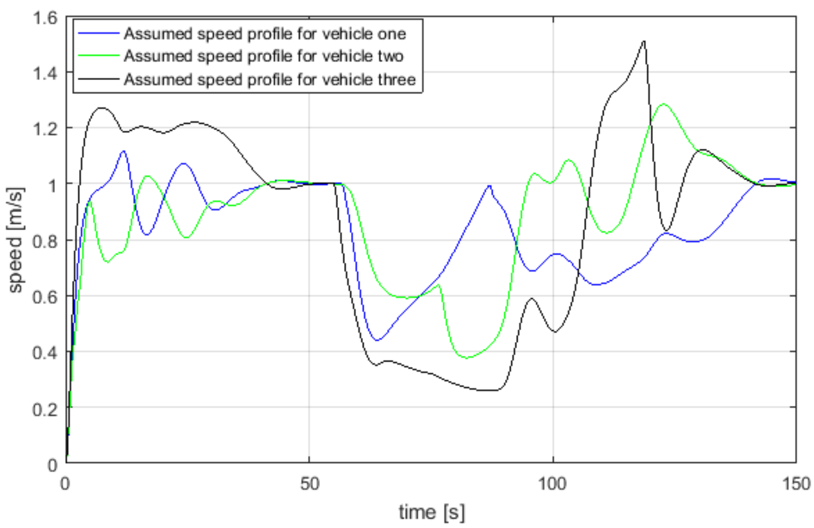


FIGURE 5.11: USV speed profiles assumed during swarm aggregation evolution for three USVs

2. The overall guidance system takes into account the physical limits of the vehicle i.e. in the current study the maximum and minimum manoeuvring speeds of *Springer* are being considered by setting the value of $K_{sat} = 0.5$.

It should be noted that formation is a function of initial position and evolution along a desired reference. In Figure 5.12 and Figure 5.15, actual surge speed and heading angle is compared with reference speed and orientation for three and four USVs framework

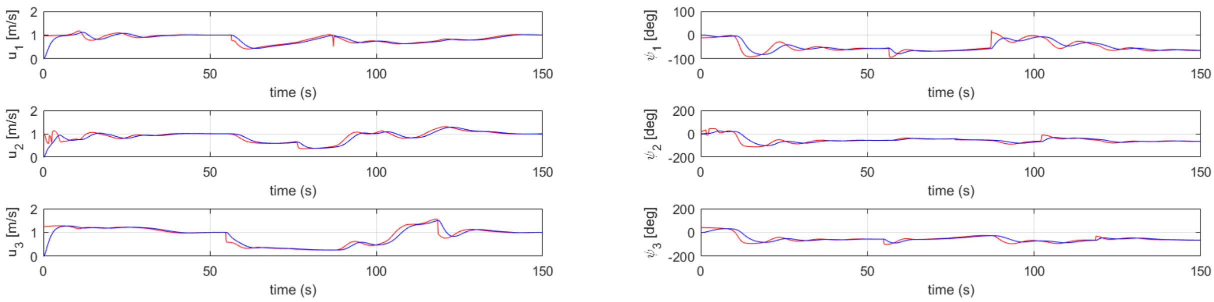


FIGURE 5.12: USV speed and heading profiles during swarm aggregation combined with path-following guidance for three USVs

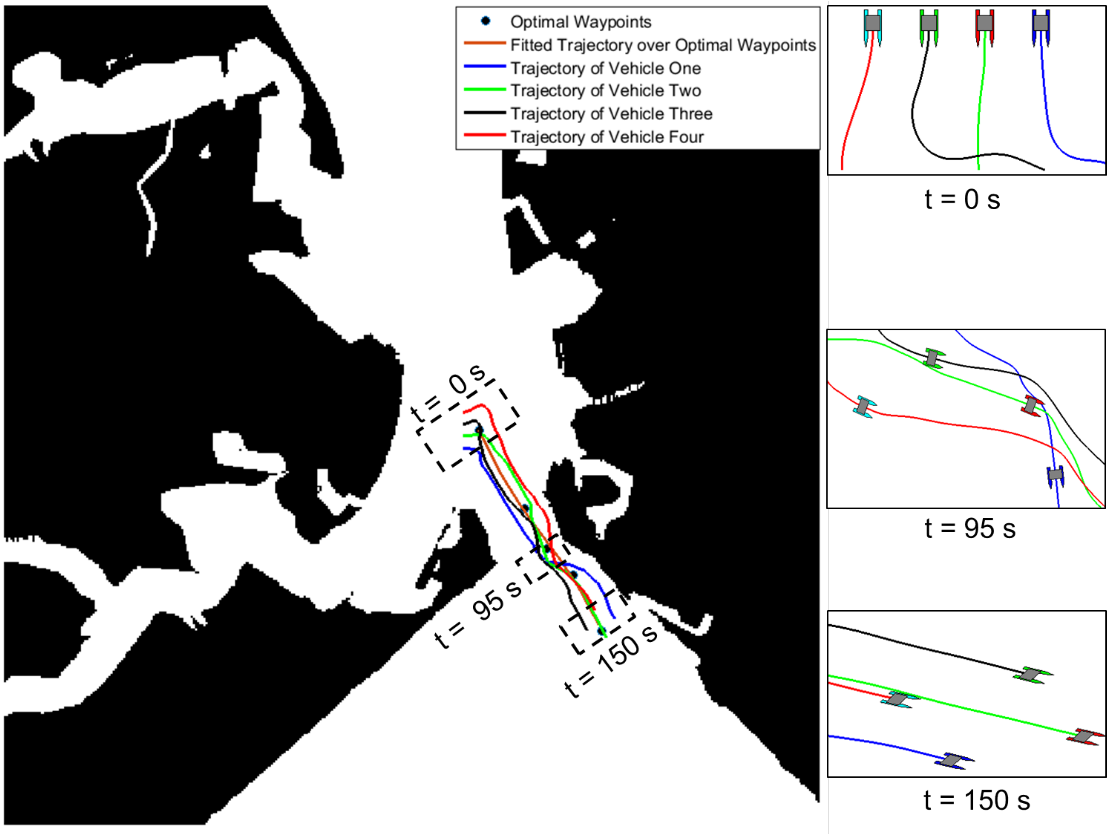


FIGURE 5.13: USV motions during swarm aggregation combined with path-following guidance for four USVs

respectively. In order to highlight the effectiveness of the combined approach, physical limits of an USV i.e. *Springer* is accounted in the guidance system by bounding the maximum and minimum manoeuvring speed between 0.2 m/s and 1.4 m/s as shown in Figure 5.11.

5.6 Discussion

In Fig. 5.10, the experiments are being conducted for a swarm of three USVs in a practical maritime environment. The robots are initially configured by placing them parallel to each other and then the robots evolve during the motion using attractive and repulsive potential functions derived from equation 5.14 which is defined as:

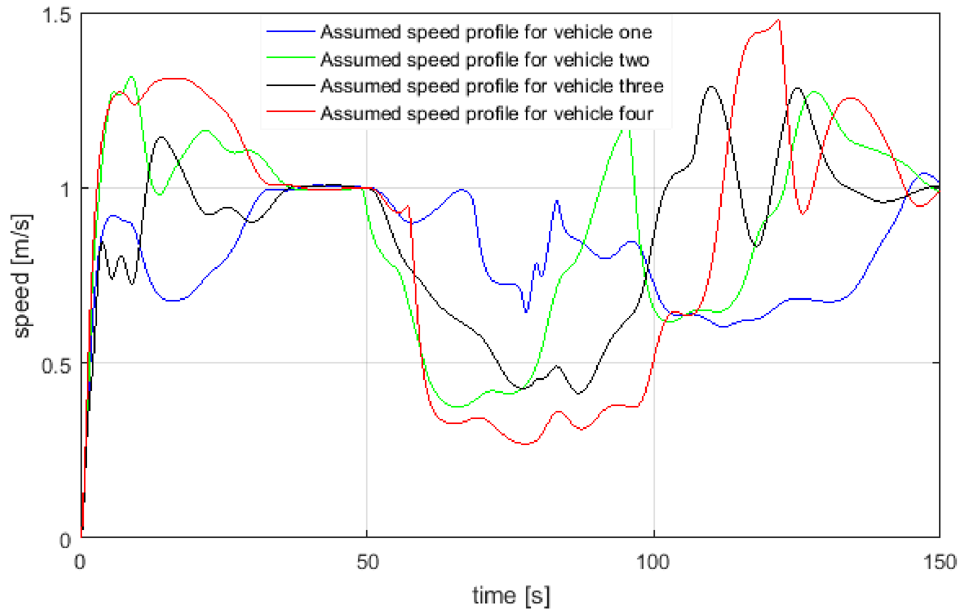


FIGURE 5.14: USV speed profiles assumed during swarm aggregation evolution for four USVs

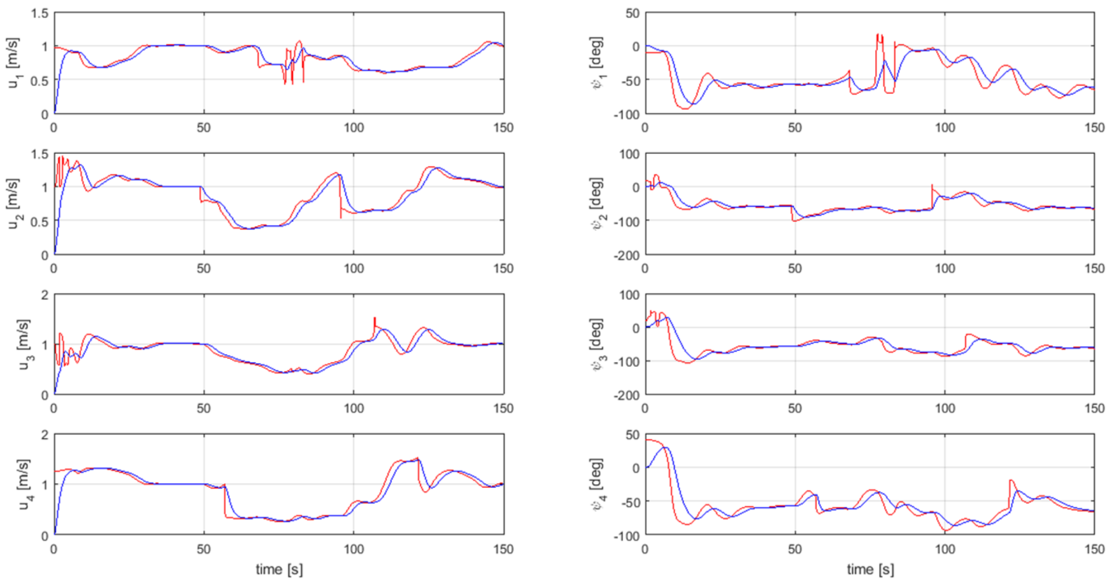


FIGURE 5.15: USV speed and heading profiles during swarm aggregation combined with path-following guidance for four USVs

$$
\begin{aligned}
g_a(d) &= \alpha \\
g_r(d) &= \frac{\beta}{d - 2\eta}
\end{aligned}
\tag{5.16}
$$

where d is the Euclidean distance between two robots $\|x_i - x_j\|$. In addition to this, the internal collision among the vehicles is determined by the repulsive function which determines that vehicles remain at certain distance from each other i.e. a distance of more than 2η in all cases. This additional term has the format $g_{ca}(d)$ which is defined as:

$$g_{ca}(d) = \frac{2\eta - d}{d^2} \tag{5.17}$$

which holds for the condition $0 \leq d \leq 2\eta$

The robots have to follow the parametrised curve from the equation 5.1. It should be noted that the formation centroid converges to the reference path showing that the proposed approach is effective in nature. Furthermore, in Fig. 5.12, for each vehicle in a swarm of three USVs, the actual surge speed and heading angle (blue lines) are compared with the generated speed and orientation references (red lines); u_1 and ψ_1 correspond to the blue vehicle, u_2 and ψ_2 correspond to the green vehicle and u_3 and ψ_3 correspond to the red vehicle. It should be noted that despite the presence of oscillations in the reference signals, the tracking of surge speed and orientation by means of dynamic controller is achieved by the proposed approach.

Similarly, In Fig. 5.13, the experiments are being conducted for a swarm of four USVs in a practical maritime environment to track a reference path based on the parametrised equation. Furthermore, in Fig. 5.15, for each vehicle in a swarm of three USVs, the actual surge speed and heading angle (blue lines) are compared with the generated speed and orientation references (red lines); u_1 and ψ_1 correspond to the blue vehicle, u_2 and ψ_2 correspond to the green vehicle, u_3 and ψ_3 correspond to the black vehicle and u_4 and ψ_4 correspond to the red vehicle.

5.7 Concluding remarks

In this chapter, the integration of constrained A* path planner with virtual target path following guidance for multi-agent USV is reported. By way of introduction, an exhaustive study of different approaches proposed in the literature has been discussed. Currently there are few works which have proposed the hybrid cooperative framework for multi USV systems.

In this context, the main contributions of the current chapter are summarised as follows:

1. Integration of a constrained A* approach with a decentralised virtual target guidance approach combined with a APF based swarm aggregation technique for the cooperative navigation of multi USVs.
2. Combining the important features of optimal path, computational time and external collision avoidance with shoreline within the initial approach proposed by Bibuli et al. (2014).

3. A constrained practical maritime environment is being considered to guide and navigate the swarm of USVs through a narrow channel on Portsmouth harbour which has not been studied till now in the literature.

4. Towards the collision avoidance with the external shoreline, a shore profile as a set of repulsive fixed points is being included in the existing approach proposed by Bibuli et al. (2014) and a modified approach is proposed.

The easiness of integration, given by the modular composition of path-planner, vehicle formation aggregation and formation guidance procedures makes it applicable for real time marine environment. A set of results on three and four USVs demonstrates the validity of the combined approach with respect to robustness and collision avoidance. The robustness of the collision avoidance solution and to evaluate the functional limits of the adopted approach has already been analysed using Monte Carlo simulations in Bibuli et al. (2014). The results of the current chapter has been published as a conference article by the International Federation of Automatic Control (IFAC) which is shown in Appendix B.

Chapter 6

Conclusions and Recommendations for Future Work

"The light of past discovery draws me forward. Its shining light guides me to the glory of exploration"

Sir Francis Drake

This chapter summarises the contributions presented in the thesis and introduces perspectives of future research to further enhance the current work.

6.1 Review of the contributions and conclusions

Cooperative navigation of a fleet of USVs is an important research area owing to its large number of potential applications. Cooperative behaviour refers to guiding and navigating a group of agents coordinating in a global framework to achieve mission objectives globally and locally. In this context, the current thesis provides a hybrid framework towards multi agent USV guidance and navigation by integrating a constrained A* path planner with a virtual target path following guidance in addition to a APF based swarm aggregation algorithm for a swarm of USVs. This hybrid framework takes into account the features of formation control and cooperative motion planning with the final objective of guiding and navigating a fleet of USVs in a constrained maritime environment. To achieve this aim, the problem is broken into two layers where the higher layer of the planning involves the development of a computationally effective, safe and optimal path planner in a constrained maritime environment. This is one of the major contributions of the current work where such an novel path planner has not been proposed in the literature. The second part of the two layered architecture is the integration of the virtual target based guidance approach combined with an APF based swarm aggregation approach towards multi USV navigation. The major contribution is the inclusion of a shoreline effect to avoid the external collision of the USVs by considering the shoreline as a set of repulsive fixed points within a certain distance and concurring in the vehicle motion evolution. This modification is being tested for a set of three and four USVs navigating in a constrained channel of Portsmouth harbour. The hybrid framework was found robust, effective and optimal in a practical maritime environment which makes it highly appealing for practical application at sea.

6.1.1 Constrained A* path planner

There is a continuous need for safe, optimal and robust path planners in the area of navigation of USVs which can be effectively implemented in a practical maritime environment. In order to understand the current requirement, a detailed literature review is conducted in the area of USVs to identify the gaps. Chapter 2 covers the area of path planning of single and multiple USVs to identify these gaps. In order to establish and benchmark the efficiency of heuristic path planners over local path planners, Chapter 3 covers the area of comparing the computational performance in simulations. In this Chapter, the main aim is to establish the computational supremacy of the Dijkstra algorithm over the APF in a practical maritime environment. Based on this, a safety distance constrained A* path planner is proposed in Chapter 4. This novel and computationally efficient path planner was initially benchmarked for different safety distances and a suitable safety distance is chosen for the current study. The novel path planner is tested in different environmental conditions and found to be computationally efficient and robust in providing optimal solutions to the objective of generating safe path for an USV.

Until now in previous works related to the path planning of an USV, such an approach of developing a computationally effective and safe path planner has not been considered. The main idea is to constrain the area around an USV with a safety distance circle leading to exploration of a less number of nodes in the generation of the path. This leads to a decrease in computational time in determining the path in a map based on the concept of an occupational grid. This result, is a preliminary step and an input to the modified guidance and swarm approach for multi USV navigation.

6.1.2 Hybrid framework for multi USV navigation

Formation control and cooperative motion planning are the two most popular areas of research studied in developing a framework for multi robot guidance, navigation and control. Although many research initiatives are implemented in the field of aerial and ground robotics, there is a strong need to develop robust framework for the navigation, guidance and control for the swarm of marine robots in the maritime environment. In order to take care of the current requirement, the current thesis proposes a novel hybrid framework for the navigation and guidance of a swarm of USVs in the constrained practical maritime environment of Portsmouth harbour.

In the previous work pertaining to the swarm of USVs, where the current thesis is focused on, such an hybrid approach has not been taken into consideration. The main idea in developing this approach is to combine a constrained A* path planner with the virtual target path following guidance and swarm aggregation approach for the multi USV navigation in a practical maritime environment. In addition to this, the existing approach proposed by Bibuli et al. (2014) is modified for external collision avoidance by considering the shore profile as a set of repulsive fixed points. The result is tested for a swarm of three and four USVs and the modular composition of the path planner, the guidance approach and the swarm aggregation approach makes it applicable for practical usage in the maritime environment.

6.2 Future work

This thesis proposes a hybrid framework towards navigation and guidance of a swarm of USVs in a constrained practical maritime environment. The main contributions previously presented have been developed considering several assumptions related to the model of the vehicles, sensor information, communication constraints etc.. Consequently, future research directions should focus on relaxing some of the assumptions to consider more realistic situations.

6.2.1 Perspectives in path planning

The path planner proposed in this thesis takes into consideration that the USVs know the position of the moving obstacles over time. This assumption is consistent to the fact that USVs are equipped with the precise measurement units for the navigation. Nevertheless, an important extension of the proposed path planner in Chapter 4 is to incorporate the measurements of the moving vessels from a nautical chart and test the robustness of the current path planner with respect to some realistic data in a practical maritime environment. Another important extension is to consider heading angle constraint for the USV in cases, where path smoothness is more important than the computational time. This converts the problem of path planning from a R^2 to $SE(2)$ approach. A hybrid approach of combining the proposed path planner with a reactive path planning approach in scenarios involving close encounter situations can be another extension of the current work.

6.2.2 Perspectives in a multi USV framework

The hybrid framework towards multi USV navigation and guidance proposed in the Chapter 5 are tested for three and four USVs. Future studies can take into account the sea surface currents into an online planning layer of the framework by considering the disturbance as a Gaussian noise signal to the orientation and surge speed of the each USV involved in the swarm. Another extension is to test different control approaches after adding Gaussian noise towards zeroing of the along track and cross track errors. An extension of the proposed approach where heterogeneous marine robots i.e. AUVs and USVs can cooperate, taking into account the communication constraint of the acoustics for underwater communication, will help in increasing the current autonomy levels of the marine robots.

Appendix A

Stability of the multi USV framework

To understand the swarming algorithm developed for the fleet of USVs, the initial concept proposed by Gazi and Passino (2003) and Gasparri et al. (2012) needs to be reviewed. This section has been extensively explained in Bibuli et al. (2014). For a swarm of n robots with a network topology encoded by a undirected fully connected graph $G = \{V, E\}$, the dynamics of each robot i is defined by

$$x_i = \sum_{j \neq i} g(x_i - x_j) \tag{A.1}$$

where $g(\cdot)$ is the interaction function representing the attraction and the repulsion between two robots in the neighbourhood. Let us denote the $g_a(\cdot) : \mathbb{R}^+ \to \mathbb{R}^+$ and $g_r(\cdot) : \mathbb{R}^+ \to \mathbb{R}^+$ as the attraction and repulsive functions respectively. The interaction function can then be defined as

$$g(\cdot) = -y[g_a(\| y \|) - g_r(\| y \|)], \forall y \in \mathbb{R}^m \tag{A.2}$$

This important feature of the interaction function being odd i.e. $g(y) = -g(-y)$ leads to the aggregation behaviour where $y \; g_a(\| y \|)$ represent the actual attraction while the $y \; g_r(\| y \|)$ represent the actual repulsion acting in the opposite direction on the same line of the action.

Let us consider some assumptions for the attractive and repulsive functions which are as follows

Assumption 1. There exist a unique distance δ corresponding to which we have $g_a(\delta) = g_r(\delta)$. Also, we have $g_a(\| y \|) \geq g_r(\| y \|)$ for $\| y \| \geq \delta$ and $g_r(\| y \|) > g_a(\| y \|)$ for $\| y \| < \delta$.

Assumption 2. There exist corresponding functions $J_a(\| y \|) : \mathbb{R}^+ \to \mathbb{R}^+$ and $J_r(\| y \|) : \mathbb{R}^+ \to \mathbb{R}^+$ such that $\nabla_y J_a(\| y \|) = y g_a(\| y \|)$ and $\nabla_y J_r(\| y \|) = y g_r(\| y \|)$.

Assumption 3. The attraction and the repulsion functions needs to fulfill the following requirements

$$g_a(\| y \|) \geq \alpha; \qquad g_r(\| y \|) \leq \frac{\beta}{\| y \|} \tag{A.3}$$

with α, $\beta \in \mathbb{R}^+$

In Gazi and Passino (2003), the following properties were proven

1. The barycenter $\bar{x}$ of the swarm is stationary over time.
2. The swarm converges to a steady configuration.
3. The swarm moves towards and remain within a bounded region. The characterisation of the bounded region is provided by Gazi and Passino (2003)
4. The swarm reaches the bounded region in finite time.

The single vehicle path follower developed by Bibuli et al. (2014) and the swarming algorithm described above are combined with control input to each USV defined as follows

$$\dot{x}_i = u_i^s + u^g \tag{A.4}$$

where u_i^s is the control effort for each USV to reach a collective behaviour while the u^g refers to expected trajectory of the fleet centroid computed with reference to path following algorithm as

$$u^g = \begin{bmatrix} u^* \cos \psi^* \\ u^* \sin \psi^* \end{bmatrix} \tag{A.5}$$

The positive constraint is imposed in the reference speed u^* since marine vehicles are having one directional forward surge motion. In terms of the proposed framework, resulting velocity vector maintain the π sector direction of the path following velocity contribution i.e. $\angle(\dot{x}_i) \in [\angle(u^g) - \pi/2; \angle(u^g) + \pi/2]$. The condition $\| u_i^s \| \leq \| u^g \|$ has to be satisfied in order to avoid motion inversions and steering behaviour generated by change in robots direction. In case of a time variant desired path following speed profile $u_g^* = u^*(t)$, the parameter k is tuned over time to satisfy the positive surge speed constraint. This is achieved by adopting $k = \tilde{k}u^*(t)$ with $0 < \tilde{k} < 1$ leading to enforcement of the constraint

$$\| u_i^s(t) \| < \| u^g \| \; \forall t \geq 0 \tag{A.6}$$

In order to understand the stability property, the analysis is carried out by navigating the swarm in a obstacle free environment. More specifically, the maximal discrepancy between the desired heading ψ^* and the angle of the velocity vector for any USV by assuming two control terms to be orthogonal vectors is defined as

$$\Delta\psi = max_{i \in 1,\ldots,N} \left\{ \arctan\left(\frac{\| u_i^s(t) \|}{\| u^g(t) \|} \right) \right\} \tag{A.7}$$

This discrepancy term $\Delta\psi$ affects the guidance of the swarm centroid during the swarm aggregation and is rewritten in the Lyapunov function as

$$\dot{V}_\nu = \nu U \sin\left(\psi^* + \Delta\psi - \psi_f\right) = \nu U \sin\left(\Phi(\nu) + \Delta\psi\right) \tag{A.8}$$

The term $\sin\left(\Phi(\nu) + \Delta\psi\right)$ can be rewritten as

$\frac{1}{\sqrt{(\| u^g(t) \|^2 + \| u_i^s(t) \|^2)}} [\| u^g(t) \| \sin\Phi(\nu) + \| u_i^s(t) \| \cos\Phi(\nu)]$

where $\| u^g(t) \| \equiv U$; which is substituted in the Eq.A.8 leading to

$$\dot{V}_\nu = \frac{\nu U}{\sqrt{(U^2 + \| u_i^s(t) \|^2)}} [U \sin\Phi(\nu) + \| u_i^s(t) \| \cos\Phi(\nu)] \tag{A.9}$$

Being the term $\| u_i^s(t) \|$ positive and bounded and $| \phi(\cdot) | < \frac{\pi}{2}$ by definition, the term $\tilde{U} \cdot (=) \sqrt{U^2 + \| u_i^s(t) \|^2}$ is assumed and the $\dot{V}_\nu$ is rewritten in terms of disturbance ϵ for path follwing module as

$$\dot{V}_\nu = \frac{\nu U}{\tilde{U}} [U \sin\Phi(\nu) + \epsilon] \tag{A.10}$$

To achieve the stability the criterion thereby becomes $\dot{V}_\nu \leq 0$ leading to the condition

$U \sin\Phi(\nu) + \epsilon \leq 0$

Hence the path following error component ν is bounded by the limit value

$\tilde{\nu} = \Phi^{-1}(\sin^{-1}(\frac{\epsilon}{U}))$

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